# The Limits of Arbitrage: Evidence from Fundamental Value-to-Price Trading Strategies*

**K.C. John Wei**
Department of Finance
Hong Kong University of Science and Technology
Clearwater Bay, Kowloon, Hong Kong
Tel: (852)-2358-7676; fax: (852)-2358-1749
Email: johnwei@ust.hk

**Jie Zhang**
Department of Finance
Hong Kong University of Science and Technology
Clearwater Bay, Kowloon, Hong Kong
Tel: (852)-9742-4489; fax: (852)-2358-1749
Email: zjking@ust.hk

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## Abstract

Shleifer and Vishny (1997) argue that arbitrage can be both costly and risky. As a result, arbitrageurs will not exploit arbitrage opportunities if the costs and risk of arbitrage exceed its benefits, thereby allowing mispricing to survive for long periods of time. Frankel and Lee (1998) document that the fundamental value-to-price ($V_f/P$) ratio predicts future abnormal returns for up to three years, where $V_f$ is an estimate of fundamental value based on a residual income model that uses analyst earnings forecasts. Ali, Hwang and Trombley (2003a) further show that their results seem consistent with the mispricing explanation rather than with the risk explanation of the $V_f/P$ effect. Thus, the $V_f/P$ effect provides a good means to examine the limits of arbitrage. We find that the $V_f/P$ effect is extremely weak in stocks of old age (measured by the history of listing), low investor sophistication, high divergence of opinion, high idiosyncratic return volatility, and high transaction costs. Further analysis shows that firm age, earnings quality, and divergence of opinion have incremental power beyond other measures of risk in explaining the cross-sectional variation in the $V_f/P$ effect. Our results appear to be consistent with the argument of the limits of arbitrage. More specifically, when arbitrageurs exploit arbitrage opportunities, they seek to avoid mispriced stocks with the greatest arbitrage risk.



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## 1. Introduction

One of the fundamental assumptions in financial economics is that arbitrage requires no capital and is risk-free. When security prices deviate from fundamental values, crowds of smart investors jump into the market to buy cheap stocks and sell expensive ones. By taking the largest positions possible, these arbitrageurs soon bring prices back to fundamental values, thereby enjoying risk-free returns. In real financial markets, arbitrage is, of course, like spinose roses, attractive but dangerous.[1] In other words, arbitrage has its limitations. When mispricing occurs, strategies designed to exploit this opportunity are both risky and costly, thereby allowing mispricing to survive for long periods of time. Shleifer and Vishny (1997) argue that arbitrage is costly and that any systematic mispricing can be quickly traded away only in situations where the benefits of arbitrage exceed its costs. Liu and Longstaff (2004) document that when the real-world feature of collateral constraints is introduced, arbitrage becomes risky and the optimal strategy for an arbitrageur is to take a smaller than a maximum position, allowing room for potential widening of the mispricing. Mitchell, Pulvino and Stafford (2002) point out that arbitrage is often terminated before convergence by the occurrence of an event. As a result, even when facing an obvious arbitrage opportunity, arbitrageurs may not be able to profit from it.

Frankel and Lee (1998) show that the fundamental value-to-price ($V_f/P$) ratio predicts cross-sectional stock returns for up to three years, where $V_f$ is the estimate of fundamental value based on a residual income model that uses analyst earnings forecasts. The intuition behind the $V_f/P$ effect is that $V_f$ reflects investors' valuation of a stock, and thus $V_f/P$ serves as an indicator of mispricing to judge whether the stock is cheap or expensive. The $V_f/P$ strategies of buying the most undervalued stocks and shorting the most overvalued stocks will produce arbitrage returns when prices converge towards fundamental values. Frankel and Lee (1998) also show that abnormal returns to $V_f/P$ strategies are not attributed to the book-to-market ratio, market capitalization, or systematic risk measured by the market beta. Ali, Hwang and Trombley (2003a) further document that the $V_f/P$ effect is partially concentrated around future earnings announcements and survives an extensive set of risk proxies. The evidence appears to support the mispricing explanation rather than the risk explanation of the $V_f/P$ effect. Xie (2004)

[1] Take an example of the bankruptcy of Long-Term Capital Management (LTCM) and Orange County. Did they perform pure arbitrage strategies? Yes, but they did not live through the "darkest before dawn" and ended with billions of dollars of losses. Ironically, had LTCM and Orange County not liquidated their assets involuntarily, and had the hold-to-maturity strategies been maintained, they would have avoided losses and even generated profits. See Jorion (1997), Miller and Ross (1997), and Lowenstein (2001) for more details.

examines the movement of $V_f/P$ and finds that only a small subsample of stocks with extreme $V_f/P$ exhibits price convergence and that returns to $V_f/P$ strategies are mainly driven by this subsample. Obviously, arbitrage risk plays an important role in preventing the price convergence of stocks. Therefore, the $V_f/P$ effect provides a good means to examine the limits of arbitrage.

There exist three categories of risk that result in the limits of arbitrage: namely, fundamental risk, noise trader risk and implementation risk. Fundamental risk is simply the risk that arbitrageurs may be wrong about the fundamental values of their positions. We measure this risk at both the firm level and the investor level by looking at firm maturity, earnings quality, investor sophistication, and divergence of opinion. Noise trader risk is the risk that the mispricing being exploited by arbitrageurs worsens in the short run (see De Long et al. (1990) and Shleifer and Vishny (1997)). We use idiosyncratic return volatility computed from the CAPM as a proxy for idiosyncratic noise trader risk. Implementation risk is the risk that arbitrage returns are completely eroded by transaction costs or short-sale constraints. We use a number of proxies for liquidity and institutional ownership to measure implementation risk. In actual financial markets, arbitrage resources are concentrated in the hands of a relatively few specialized and poorly diversified traders. These arbitrageurs always face many frictions and constraints that deter their arbitrage activities. Moreover, they often act as managers who invest for others rather than just invest their own money. Principal-agent problems arise and make arbitrage even more difficult. Since the $V_f/P$ effect is attributable to the convergence of mispricing, arbitrage strategies based on $V_f/P$ should work only for stocks with low arbitrage risk and should not work for stocks with high arbitrage risk.

The objective of this paper is to examine empirically the limits of arbitrage on $V_f/P$ strategies. More specifically, we investigate the effects of arbitrage risk on the $V_f/P$ anomaly. Our results are consistent with the prediction of the limits of arbitrage. We find that $V_f/P$ strategies do not work for stocks with extremely high arbitrage risk measured by firm maturity, earnings quality, investor sophistication, divergence of opinion, idiosyncratic return volatility, liquidity, and institutional ownership. When we consider all these arbitrage risks and exclude those stocks with any of these arbitrage risks in the highest quintiles, the $V_f/P$ effect improves markedly. Moreover, this $V_f/P$ strategy succeeds even during the Internet bubble period when a $V_f/P$ strategy on all stocks is disastrous. Our evidence confirms the view of the limits of arbitrage that high transaction costs, high noise trader risk, and high fundamental risk inhibit arbitrage activities and prolong the process of prices converging to their fundamental values.

Our research contributes to the literature on the limits of arbitrage by empirically identifying the effects of different types of arbitrage risk on the $V_f/P$ effect in a large sample. Numerous recent studies demonstrate that arbitrage opportunities or mispricing could be sustained in equilibrium when financial markets have frictions or imperfections.[2] Liu and Longstaff (2004) further demonstrate that, in markets where arbitrage is possible but risky, even when the optimal strategy is employed, arbitrage typically leads to losses before the final convergence and arbitrage returns may be indistinguishable from the returns of a conventional portfolio. This echoes previous studies on arbitrage risk.[3] However, identifying the specific factors of arbitrage risk and determining how such risk quantitatively affects the returns from arbitrage remain empirical questions. Using a number of direct measures for arbitrage risk, we find that $V_f/P$ strategies are very profitable and less risky when arbitrage risk is low, highlighting the importance of such risk in implementing arbitrage strategies.

Prior empirical studies investigating the effect of arbitrage risk on trading strategies that exploit opportunities in mispricing focus mainly on transaction costs or noise trader risk, and not much on fundamental risk. Furthermore, these studies are usually limited to small samples or short periods of time because of the lack of universally accepted arbitrage opportunities in large samples and over long periods of time.[4] Our paper extends the literature by introducing a well-documented arbitrage strategy based on $V_f/P$. This strategy applies to quite a large sample of stocks and earns long-term profits when price convergence occurs gradually. Ali, Hwang and Trombley (2003b) also employ a prevalent and long-term strategy, the book-to-market strategy, to examine the relation between arbitrage risk and arbitrage returns. However, their study relies on the validity that the book-to-market effect is due to mispricing. Their evidence does not rule out the possibility that the book-to-market ratio is a proxy for certain systematic risk, suggesting that their strategy might not be real arbitrage.[5] The distinction between our paper and theirs is that we examine arbitrage strategies based on the well-known mispricing of $V_f/P$ with a larger set

[2] See, for example, Basak and Croitoru (2000) and Loewenstein and Willard (2000).
[3] See, for example, De Long et al. (1990, 1991), Shleifer and Vishny (1997), and Barberis and Thaler (2003).
[4] See, for example, Knes and Ready (1996), Pontiff (1996), Barber et al. (2001), Baker et al. (2002), Mitchell et al. (2002), Ofek et al. (2002), and Lamont and Thaler (2004).
[5] Fama and French (1993) argue that the book-to-market effect can be explained by the Fama-French three-factor model. This suggests that the book-to-market ratio may be a proxy for distress risk.

of proxies for arbitrage risk. Another distinction is that we find that transaction costs are crucial to arbitrage profits.

The remainder of this paper is organized as follows. In Section 2, we briefly review the measures of arbitrage risk identified in the literature and develop our hypotheses. We then introduce the estimation of the fundamental value ($V_f$) of a stock based on a residual income model in Section 3. Section 4 describes our data and sample as well as the $V_f/P$ strategies. Section 5 reports our empirical results, while Section 6 concludes the paper.

## 2. Arbitrage Risk and Measurements

Numerous studies and many painful real-life lessons suggest that arbitrage is both risky and costly, because assumptions made glibly in classical finance theory do not hold under arbitrage conditions. For instance, let us consider a hedge fund manager who implements a textbook arbitrage strategy on the mispricing of stocks.[6] Assume that the mispricing is guaranteed to converge sooner or later, that financial markets are frictionless and that the manager has unlimited capital resources. The manager can simply maintain the hold-to-maturity strategy to realize the risk-free arbitrage return. The greater the mispricing, the greater the incentive for the manger to engage in this arbitrage. However, in real financial markets, many practical issues arise and constrain the manger from engaging in arbitrage activities. The risks associated with the factors that affect arbitrage returns are enumerated in the following.

### *2.1 Fundamental risk*

Probably the first question that quickly comes into the manager's mind is: "Does the mispricing truly exist?" If the mispricing does not exist, the prices may never converge to the fundamental values that the manager estimates and the arbitrage strategy may not generate any profit. The manager's problem reflects exactly the fundamental risk or valuation uncertainty in arbitrage, which means that arbitrageurs are uncertain about the true fundamental values of their arbitrage positions. When arbitrage strategies are implemented on stocks based on $V_f/P$, we can however evaluate this risk uncertainty from the perspectives of firms, analysts, and investors.

First, it is plausible that firms with longer histories, usually in more mature industries, have more information available to arbitrageurs (Zhang (2006)). Firm age (*AGE*), measured as the

[6] As mentioned in Liu and Longstaff (2004), a textbook strategy exploits an arbitrage opportunity by taking long and short offsetting positions and holding them until convergence.

number of months since the firm appeared in the Center for Research in Securities Prices (CRSP) database, provides a good proxy for information or valuation uncertainty at the firm level. Second, we follow Francis et al. (2003) to proxy this information/valuation uncertainty with a measure of earnings quality (*AQ*), which is the standard deviation of the residuals obtained from rolling cross-sectional regressions of the modified Dechow and Dichev (2002) model.[7]

Finally, we use two proxies based on analyst information and one proxy based on professional investor information to measure information/valuation uncertainty. A natural proxy is analyst coverage (*NANAL*), which is measured by the number of analysts following a firm. Empirical evidence shows that a large number of analysts following a firm is associated with a large number of sophisticated market participants and greater information availability about the firm, which leads to less valuation uncertainty (Brennan et al. (1993) and Hong et al. (2000)). We also use the number of institutional investors (*NINST*) as an alternative proxy for investor sophistication for a robustness check (Chen et al. (2002)). However, a more sophisticated investor base is not sufficient for arbitrageurs to value stocks more accurately. Even when a stock is mainly traded by experienced investors, the value of the stock can still be ambiguous if there are large differences of opinion among investors. We therefore follow Diether, Malloy and Scherbina (2002) and use the dispersion in analysts' earnings forecasts (*DISP*) to measure the divergence of opinion among investors. In the prior literature, this measure was widely used as a proxy for the degree of consensus among analysts or market participants and hence as a measure for valuation uncertainty (Barron and Stuerke (1998)).

Our intuition for using the above proxies (*AGE*, *AQ*, *NANAL*, *NINST* and *DISP*) for fundamental risk is very straightforward. The degree of firm maturity and the quality and reliability of earnings are the major signals that rational arbitrageurs use to determine fundamental value and, in turn, to exploit arbitrage opportunities. Furthermore, active trading involving sophisticated investors and a low divergence of opinion among them accelerate the rational convergence of prices toward fundamental values, and such acceleration benefits arbitrageurs. The above proxies are also used in the recent literature to measure information uncertainty (Francis et al. (2003), Jiang et al. (2005) and Zhang (2006)).

[7] This measure captures the mapping of earnings into cash flows: the weaker the mapping, the poorer the quality of earnings.

*2.2 Noise trader risk*

Even when fundamental risk is subtle, the hedge fund manager is confronted with another problem. If the mispricing indeed exists, price convergence may still not occur in a timely and smooth manner. Even worse, the mispricing may widen rather than narrow in the short run because of the actions of irrational noise traders. If this widening were to happen, the manager would experience mark-to-market losses on the arbitrage. Sometimes, price fluctuations can be big trouble for the manager, because the losses can be very severe. This problem was identified by De Long et al. (1990) and Shleifer and Vishny (1997) as noise trader risk.

Arbitrage is usually the province of a relatively small number of highly specialized investors. Shleifer and Vishny (1997) argue that arbitrageurs are risk averse and are concerned about the idiosyncratic risk of their arbitrage positions, which are often poorly diversified.[8] They further note that arbitrageurs often manage money for outside investors (the so-called separation of brain and capital). Arbitrageurs who manage other investors' money care about short-term performance, because investors who provide capital are often so myopic and unknowledgeable that they evaluate arbitrageurs' strategies based on short-term returns. After arbitrageurs take positions because of mispricing, it is very common that noise traders may push prices further away from their fundamental values, inducing unwise investors to withdraw their funds at the most tenuous but promising time when the mispricing is at its widest divergence (Warther (1995)). In the above situation, arbitrageurs are forced to liquidate their positions prematurely and consequently suffer losses. Therefore, arbitrageurs are very likely to forsake arbitrage opportunities in highly volatile stocks, although the mispricing in these stocks might be quite extensive.

In addition to the lack of diversification and principal-agent problems, several other practical concerns deter arbitrage activities in highly volatile stocks. Consider the hedge fund manger again. What if the manager generates a liability that must be secured by collateral while taking positions in arbitrage? The manager faces the margin risk that creditors call partial payment when the collateral value deteriorates (Liu and Longstaff (2004)). What if the manager cannot continue to borrow shares for taking short positions to maintain a risk-neutral position?[9] These factors result in the same consequence that the manager has to worry about adverse intermediate

[8] The analysis process in selecting stocks for investment is so costly that arbitrageurs only include a limited number of stocks in their portfolios.
[9] This is called the short squeeze risk. See D'Avolio (2002) and Geczy et al. (2002).

price movements from the minute the arbitrage is started to avoid the risk of involuntary liquidation.

Naturally, idiosyncratic stock return volatility is a good proxy for noise trader risk by definition. Unlike systematic volatility, idiosyncratic volatility does not compensate arbitrageurs for higher expected returns, or, alternatively, it cannot be eliminated by hedging. Moreover, since arbitrageurs are poorly diversified, idiosyncratic volatility adds a lot to the total volatility of their portfolios. In selecting mispriced stocks to exploit arbitrage, arbitrageurs would consider the expected idiosyncratic volatility during the holding period. To estimate a stock's expected idiosyncratic volatility (*IVO*), we regress one-year daily returns on CRSP value-weighted market returns (i.e., a single-factor CAPM) and compute the standard deviation of the residual terms.

*2.3 Implementation risk*

Finally, transaction costs of arbitrage, which are related to implementation risk, are non-trivial. The manager who exploits mispricing should fully balance benefits and costs just before taking action. When stocks are mispriced, transaction costs are sometimes high enough to limit the desire of arbitrageurs to get involved in and take advantage of the mispricing. In addition, some well-documented profitable trading strategies turn out to be illusory after transaction costs are taken into account.[10] In the following, we discuss several measures of transaction costs, mainly associated with stock liquidity and short-sale costs.[11]

The first candidate is undoubtedly the bid-ask spread (*BID-ASK*), in the sense that it directly measures transaction costs in addition to brokerage commissions. However, due to the limitation of data availability (the NYSE Trade-and-Quote (TAQ) dataset starts from 1993), we also use stock prices (*PRC*) as an alternative measure since it is well established that stock prices are firmly negatively correlated with quoted bid-ask spreads as a percentage of stock prices.[12]

Aside from direct transaction costs, arbitrageurs consider the adverse impact of order flow on prices as well as the delay in processing trading. Numerous prior studies suggest that the dollar trading volume (*VOL*) measures how easily and quickly an investor can buy or sell a large block

[10] For example, Lesmond, Schill and Zhou (2004) find that momentum profits are generated disproportionately by frequent trading in high cost stocks such that transaction costs prevent profitable strategy execution.
[11] Liquidity is an elusive concept but generally denotes the ability to trade in large quantities quickly, at a low cost, and without moving the price. It has various dimensions and cannot be captured by a single measure.
[12] See, for example, Amihud and Mendelson (1986) and Keim and Madhavan (1996).

of stocks and therefore this measure is a proxy for indirect transaction costs.[13] If stocks are thinly traded, although the mispricing in them is attractive, it is difficult for arbitrageurs to execute their strategies quickly without causing an adverse price impact. In this sense, the ratio of the share trading volume to the number of shares outstanding or the turnover (*TURN*) seems to proxy for similar information as *VOL* does according to the literature.[14] Nevertheless, some studies consider *VOL* or *TURN* as a possible proxy for the intensity of disagreements with investor heterogeneity or differences of opinion,[15] suggesting an opposite inference for arbitrage from the perspective of fundamental risk. Since *VOL* is more correlated with other measures of transaction costs than is *TURN*, the imperfection of *VOL* in acting as a proxy for indirect transaction costs is less a problem than is that of *TURN*. Additionally, the adverse price impact is a function not only of trading volume, but also of return volatility. Amihud (2002) proposes to use the ratio of a stock's absolute daily return to the dollar volume to capture the impact of order flow on prices. Since Amihud's (2002) measure overstates the degree of liquidity for those stocks with zero daily returns, we modify this measure by computing the ratio of the daily price fluctuation range to the daily dollar volume (*ILLIQ*).

Short-sale constraints contribute to additional transaction costs. Constraints exist when arbitrageurs wish to sell short on overvalued stocks but are either unable to borrow shares or can only do so by receiving a low rebate rate on the proceeds from their short positions.[16] If the level of the supply of lendable stocks to arbitrageurs is low when the lender recalls the stock, arbitrageurs have no choice but to liquidate their positions prematurely, unless they can find another lender. The exposure to this "short squeeze risk" exists widely in so-called "special" stocks (D'Avolio (2002) and Geczy et al. (2002)). Ideally, the rebate rate in the equity loan market is a perfect measure for the cost of short sales. However, the data are not publicly available. Dechow et al. (2001), Chen et al. (2002) and Asquith et al. (2005) suggest using institutional ownership to measure short-sale constraints. They posit that short-sale constraints are strongly linked to the amount of shares available to borrow, and they provide evidence that when institutional ownership increases (decreases), short-sale constraints are relaxed (tightened).

[13] See, for example, Brennan and Subrahmanyam (1995), Datar et al. (1998) Chordia, Roll, and Subrahmanyam (2001), and Chordia, Subrahmanyam, and Anshuman (2001).
[14] See, for example, Atkins and Dyl (1997), Chalmers and Kadlec (1998), and Lo and Wang (2000).
[15] See, for example, Lee and Swaminathan (2000), and Hong and Stein (2003).
[16] The interest rate that institutional short sellers receive on the proceeds of the sale is called the rebate rate (Asquith et al. (2005)). Retail borrowers typically receive no interest on their proceeds.

In this paper, we follow Nagel (2005) and use the percentage of shares owned by institutions (*SINST*) as a proxy for short-sale constraints.

Firm size (*SIZE*) or the market capitalization of common equity is a mixed measure for transaction costs. Conventionally, it is a proxy for liquidity since a larger stock issue has a smaller price impact for a given order flow and a smaller bid-ask spread (Amihud and Mendelson (1986)). Lakonishok, Shleifer and Vishny (1994) use *SIZE* to proxy for arbitrage costs and investor sophistication. Zhang (2006) regards *SIZE* as a measure for information uncertainty, which is related to fundamental risk. Fortunately, no matter what kind of specific information is contained in *SIZE*, it is always true that *SIZE* gives the same prediction for arbitrage risk. To compare with prior studies, we also examine the role played by *SIZE* in measuring arbitrage risk.

### *2.4 Hypotheses*

So far, we have introduced quite a number of proxies for arbitrage risk. Not surprisingly, each proxy that is assumed to capture one specific type of arbitrage risk is also likely to capture other factors, potentially confounding our conclusions. For example, firm size could be a proxy for transaction costs, fundamental uncertainty, or investor sophistication. Short-sale constraints could be associated with either institutional ownership or differences of opinion (D'Avolio (2002)). Although our measures are not unique and are correlated with each other, it is fortunate that they have introduce only a few inconsistencies in their common ability to indicate arbitrage risk.[17] When examining the effect of arbitrage risk on arbitrage returns, it does not matter if we can perfectly distinguish these factors. Our purpose is to capture different types of arbitrage risk from as many angles as possible.

According to behavioral finance theory, the incentives of rational arbitrageurs to correct mispricing are largely subsumed by arbitrage risk, resulting in the generally poor performance of arbitrage strategies. The $V_f/P$ strategies provide a good means to identify empirically the magnitude of the effects of different types of arbitrage risk on arbitrage profits for two reasons. First, returns to $V_f/P$ strategies are arbitrage returns that are attributable to the convergence of prices to fundamental values. Second, $V_f/P$ strategies apply to large samples of stocks and long

[17] The only measure that contains contradictory inferences about arbitrage risk is turnover. From the perspective of liquidity, stocks with high turnover have low arbitrage risk. But from the perspective of differences of opinion, stocks with high turnover have high arbitrage risk. These opposite inferences are consistent with our results that turnover does not affect arbitrage returns in a clear direction (not shown).

periods of time. We expect that each of our measures of arbitrage risk, regardless the specific information it contains, will exhibit a negative relation with the returns to $V_f/P$ strategies. By incorporating various types of arbitrage risk in the sample screening, we expect that the arbitrage returns to the $V_f/P$ strategy should be improved significantly. Finally, we examine if arbitrage risk contributes to the $V_f/P$ effect incrementally and which factors among our measures are the most crucial to arbitrageurs.

## 3. Fundamental Valuation Based on a Residual Income Model

Frankel and Lee (1998) develop an approach to estimate fundamental equity value based on a discount residual income model, referred to as the Edwards-Bell-Ohlson (EBO) valuation technique (Edwards and Bell (1961), Ohlson (1990, 1995), and Feltham and Ohlson (1995)). This model expresses a stock's fundamental value as its current book equity plus the present value of expected future residual income, where residual income is the investors' expected income minus the required income that is equal to the forecasted book equity at the beginning of each period multiplied by the cost of equity capital.[18] Given the assumption of clean-surplus accounting, the residual income model could revert into the traditional dividend discount model.[19] Specifically, Frankel and Lee (1998) utilize the EBO valuation technique by simplifying the residual income model into a short-horizon version as follows:

$$V_f = B_t + \frac{(FROE_t - r_e)}{(1+r_e)} B_t + \frac{(FROE_{t+1} - r_e)}{(1+r_e)^2} B_{t+1} + \frac{(FROE_{t+2} - r_e)}{(1+r_e)^2 r_e} B_{t+2}, \tag{1}$$

where $V_f$ is a stock's fundamental value estimated at time $t$, $B_{t+i}$ is the expected book value of common equity at the fiscal-year end of year $t+i$, $FROE_{t+i}$ is the expected return on equity for year $t+i$, and $r_e$ is the estimated cost of equity capital. The last term in equation (1) is the estimate of the terminal value by assuming that the three-year ahead residual income continues into perpetuity. In theory, the residual income model should contain an infinite series of residual income. But, for practical purposes, the above three-period model might be optimal as a tradeoff between accurate income forecasts and a long time horizon.

The valuation of a stock by model (1) requires estimates of future returns on equity, future book equities and the cost of capital. In the empirical application, Frankel and Lee (1998)

[18] Investors' expected income is proxied by I/B/E/S consensus analyst forecasts on future earnings.
[19] Clean-surplus accounting requires that the change in book value of common equity from time $t$–1 to $t$ comes only from the income minus dividends during period $t$, i.e., $B_t = B_{t-1} + NI_t - DIV_t$.

estimate $FROE_t$, $FROE_{t+1}$ and $FROE_{t+2}$ using I/B/E/S one-year-ahead ($FY1$) and two-year-ahead ($FY2$) consensus earnings-per-share ($EPS$) forecasts, I/B/E/S five-year (long-term) consensus growth rates forecasts ($Ltg$), and reported COMPUSTAT (Item 60) book equity values ($B_{t-1}$ and $B_{t-2}$). They then iteratively derive estimates of future book values ($B_t$, $B_{t+1}$, and $B_{t+2}$) at the forthcoming three fiscal-year ends as follows:

$$FROE_t = FY1/[(B_{t-1} + B_{t-2})/2],$$

$$B_t = B_{t-1}[1 + FROE_t(1-k)],$$

$$FROE_{t+1} = FY2/[(B_t + B_{t-1})/2],$$

$$B_{t+1} = B_t[1 + FROE_{t+1}(1-k)],$$

$$FROE_{t+2} = [FY2(1 + Ltg)]/[(B_{t+1} + B_t)/2],$$

$$B_{t+2} = B_{t+1}[1 + FROE_{t+2}(1-k)].$$

If $Ltg$ is not available, $FROE_{t+1}$ is used to proxy for $FROE_{t+2}$. $k$ is the dividend payout ratio estimated as dividing the common stock dividends paid ($DIV_{t-1}$ or $DIV_{t-2}$, COMPUSTAT Item 21) in the most recent year by the net income before extraordinary items ($NI_{t-1}$ or $NI_{t-2}$, COMPUSTAT Item 237).[20]

Theoretically, the cost of capital ($r_e$) should be firm specific, reflecting the risk premium required by investors to hold the stock and the current risk-free rate. In practice, we estimate $r_e$ as an industry-specific rate by adding the three-factor industry risk premiums derived from Fama and French (1997) to the current annualized 30-day Treasury-bill rates.[21] The industry-specific discount rates differentiate stocks significantly enough, and meanwhile excessive estimation errors in calculating firm-specific risk premiums are avoided.

## 4. Data and Sample

In this paper, we apply a similar methodology as described in the last section to construct the fundamental value-to-price ratio ($V_f/P$) on a monthly basis. Our basic sample consists of all common stocks in the intersection of (a) the NYSE, AMEX and NASDAQ return files from

[20] Following Frankel and Lee (1998), for firms with negative earnings, dividends are divided by six percent of total assets to derive an estimated payout ratio. Six percent reflects the average long-run return on assets.

[21] Throughout this paper, we use the real-time 30-day T-bill rate when $V_f$ is estimated, instead of the average rate over the sample period used by Frankel and Lee (1998), to make our $r_e$ estimates more accurate and realistic. However, using different methods to estimate the discount rate has little effect on our results.

CRSP, (b) a merged COMPUSTAT annual industrial file including PST, full coverage and research files, and (c) the I/B/E/S summary historical file. To ensure that our monthly-updated $V_f$ is estimated based on the latest public information, we match the monthly analyst forecasts from I/B/E/S to the most recent two years' accounting data in COMPUSTAT according to the fiscal-year-end date.[22] For each month, we require that stocks have COMPUSTAT data available for $B_{t-1}$, $B_{t-2}$ and $k_{t-1}$ or $k_{t-2}$ (most recent $k$), and have *FY*1/*FY*2 *EPS* forecasts and a long-term growth forecast (*Ltg*) if available from I/B/E/S. Furthermore, we need the CRSP stock prices and shares outstanding data for each month to scale $B_{t-1}$ and $B_{t-2}$ to a per-share basis to calculate $V_f/P$.[23] Unlike in Frankel and Lee (1998) where they estimate $V_f/P$ annually by using the analyst forecasts in each May and prices and shares outstanding at the end of each June, we fully utilize the monthly-updated I/B/E/S summary historical file to calculate our $V_f/P$ based on the updated analyst forecasts, stock prices, and shares outstanding for each month. This approach enables us to obtain a larger sample with fewer constraints and without changing the sensitivity of $V_f/P$ to predict future returns (see Table 1).[24]

Though I/B/E/S began in 1976, we limit our sample period to January 1982 through December 2004 for estimating $V_f/P$ for two reasons. First, *Ltg* was not reported prior to December 1981. Second, the cross-section of stocks from 1982 on is large and has substantial variation in size and book-to-market ratios, which are helpful for our portfolio tests. Extending our sample period to 1976 does not change our results.

Following Frankel and Lee (1998) in estimating $V_f/P$, we remove stocks with negative book values, extreme *FROEs* (more than 100%), and unreasonable $k$ (more than 100%). Such stocks' fundamental values are usually unstable and are difficult to interpret in economic terms. In addition, we remove stocks with historical prices under \$5 for each month. These stocks not only have smaller analyst coverage and unstable and less meaningful $V_f/P$, but they also incur larger

[22] Specifically, we take the variable named *FY0EDATS* from the I/B/E/S summary historical file for each monthly observation of analyst forecasts, which provides the exact latest fiscal-year-end at which the accounting data have already been released to analysts. We then find the most recent two years' accounting data in COMPUSTAT by matching *FY0EDATS* with the COMPUSTAT Item *FYENDDT*, which denotes the fiscal-year-end for each annual observation. We note that *FY0EDATS* and *FYENDDT* are never missing in our sample period.

[23] Note that analyst forecasts for *FY*1 and *FY*2 are earnings-per-share (EPS) and are reported on the basis of the number of shares outstanding as of today rather than the historical EPS. To be consistent, we use the CRSP historical data and the cumulative factor to adjust prices and the number of shares outstanding (Item *CFACPR* and *CFACSHR*).

[24] For example, we do not necessarily constrain our sample to stocks with fiscal-year-ends between June and December because our methodology ensures that forecasted earnings correspond to the correct fiscal year by linking I/B/E/S with COMPUSTAT according to the fiscal-year-end.

transaction costs due to their poor market liquidity (less trading and larger bid-ask spreads), which could distort the feasibility of our trading strategies based on $V_f/P$.

## 5. Empirical Results

### *5.1 Portfolio strategies based on sorting by $V_f/P$*

We begin our analysis by forming quintile portfolios (V1 to V5) based on the one-month-lagged $V_f/P$ in each month. V5 (V1) represents the group of stocks with the highest (lowest) $V_f/P$. Panel A of Table 1 reports the time-series averages of stock characteristics over the period between January 1982 and December 2004.[25] To be included into our sample, a stock must have available data for $V_f/P$, firm size, book-to-market ratio, stock price, as well as the past six months' returns. There are a monthly average of 441 stocks in each of the quintile portfolios.

[Insert Table 1 here]

In general, there is no significant trend for firm size, book-to-market ratio, or stock price across our $V_f/P$ quintile portfolios, suggesting that $V_f/P$ represents certain properties that have few correlations with these three stock characteristics. On the other hand, when comparing V5 with V1 only, V5 stocks have slightly higher book-to-market ratios and lower stock prices. V5 stocks also earn significantly lower past returns than do V1 stocks. As a result, we need to control for the effects of those variables in our regression analyses. However, we note that both the magnitude and the signs of the differentials in these firm characteristics across V1 to V5 do not explain the substantial spreads in subsequent returns.

Panel B reports the averages of the equally weighted buy-and-hold portfolio returns for different holding horizons (n), $RET_{1:n}$, where n is from 1 month to 36 months.[26] We do not include the portfolios formed after January 2002 in calculating $RET_{1:n}$ when n > 1 ($RET_{1:1}$ is calculated using the whole sample period since portfolios are only held for one month). Panel B reports the average post-ranking market betas, which are estimated using the CRSP value-weighted index and each stock's monthly returns over the future 36 months. The results indicate

[25] For each of these characteristics, values greater than the 0.995 fractile or less than the 0.005 fractile in each month are set equal to the 0.995 and 0.005 fractile values, respectively, in order to avoid the twist of means induced by outliers.

[26] Mitchell, Pulvino, and Stafford (2002) examine the arbitrage opportunities in the negative stub value due to the mispricing in the parent company and its subsidiary. They find that a substantial subsample does not exhibit convergence because of a third party taking over either the parent or the subsidiary. Their study suggests that arbitrage risk is severe in those stocks delisted during holding periods. To avoid overstating the magnitude of the $V_f/P$ effect, we calculate portfolio returns using all available returns of individual stocks up to their delisting month.

that V5 stocks significantly outperform V1 stocks for all holding horizons.[27] The longer the holding period, the stronger the ability for $V_f/P$ to predict returns.

The last column of Table 1 reports the differences in means between the highest- and the lowest-$V_f/P$ portfolios, denoted as V5–V1. The statistical significance of these differences is assessed using the monthly time-series means and standard deviations over the sample period. The Newey and West (1987) procedure is used to correct serial correlations in the variables.

The V5–V1 portfolio earns 4.23%, 10.12% and 15.75% over one-, two- and three-year holding periods, respectively, and the returns are all significant at the 1% level.[28] Market risk cannot explain the differences in returns across the $V_f/P$ portfolios. High $V_f/P$ stocks have lower market betas than do low $V_f/P$ stocks, indicating that the returns to $V_f/P$ strategies do not appear to be compensation for bearing market risk. Other systematic risk factors cannot explain the differences in returns either. The second row of Penal B reports the intercepts (*ALPHA*) from the regressions of the monthly excess returns of quintile portfolios with a one-month holding horizon on the Fama-French (1993) three-factors and the momentum factor.[29] *ALPHA* increases monotonically with $V_f/P$ quintiles from negative to positive, resulting in a significant risk-adjusted return of 0.72% per month for V5–V1. This result suggests that the four-factor model cannot account for the return pattern of $V_f/P$ strategies. Overall, our results suggest that the $V_f/P$ effect is consistent with the mispricing explanation rather than with the risk explanation, confirming the results of prior studies (Frankel and Lee (1998) and Ali et al. (2003a)).

Figure 1 plots the 36-month buy-and-hold returns to the hedge strategy of buying the highest $V_f/P$-quintile and selling the lowest $V_f/P$-quintile each month from January 1982 through January 2002. We find that the arbitrage returns are relatively stable and mostly positive with two peaks before the mid-1990s. However, after the mid-1990s, the arbitrage returns become very volatile.

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[27] The existing literature documents only the significant return predictive power of $V_f/P$ over a one-year or longer time horizon. The short-term predictability of $V_f/P$ is very weak or insignificant. The V5–V1 returns are even negative over some short-term holding periods (see Figure 1 in Frankel and Lee (1998)).

[28] These returns are smaller than those reported in the previous literature (Frankel and Lee (1998) and Ali et al. (2003a)) partially because our method to calculate cumulative portfolio returns does not exclude those stocks that survive for less than n months after portfolio formation. The V5–V1 returns in Frankel and Lee (1998) are 3.1%, 15.2%, and 30.6% over one-, two- and three-year holding periods, respectively. If we allow for survival biases and limit our sample period to the same sample period as in Frankel and Lee (1998), our V5–V1 returns are virtually similar to those reported by Frankel and Lee.

[29] Throughout this paper, we estimate the following four-factor time-series regression for portfolio returns:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^M (MKT_t - R_{f,t}) + \beta_i^S SMB_t + \beta_i^H HML_t + \beta_i^U UMD_t + \varepsilon_{i,t},$$

where $R_{i,t} - R_{f,t}$ is portfolio *i*'s excess return, $MKT_t - R_{f,t}$, $SMB_t$ and $HML_t$ denote the standard Fama and French three factors, and $UMD_t$ denotes the Carhart (1997) momentum factor.

The $V_f/P$ strategies even incur big losses from 1997 to 2000, but recover to become very profitable after 2000. The phenomenon is very likely attributed to the "Internet mania" prevalent during the late 1990s, when investors totally forgot fundamentals in pursuit for hot technology stocks. This also partially explains why our returns to $V_f/P$ strategies are smaller than those reported by Frankel and Lee (1998), who used the 1976 to 1993 sample period.

[Insert Figure 1 here]

*5.2 Fundamental risk and $V_f/P$ portfolio strategies*

The main purpose of this study is to examine the limits of arbitrage on the $V_f/P$ effect. Since expected fundamental risk seems to be a primary concern for arbitrageurs, we firstly examine the interaction between fundamental risk and the $V_f/P$ effect. Our measures of fundamental risk include: (1) *AGE* (the number of months between the current month and the first month that a stock appears in CRSP), (2) *AQ* (the standard deviation of the residuals from the cross-sectional regressions of the modified Dechow and Dichev (2002) model over year *t*-5 to *t*-1),[30] (3) *NANAL* (the number of analysts following a stock included in I/B/E/S in the previous month), (4) *NINST* (the number of institutional owners at the end of the most recent quarter, recorded in the Compact Disclosure database),[31] and (5) *DISP* (the standard deviation of analyst *FY*1 *EPS* forecasts scaled by the absolute value of the mean forecast in the previous month, as reported in the I/B/E/S summary history file).[32] As discussed in Section 2, *AGE* is a proxy for firm maturity; *AQ* is a proxy for earnings quality; *NANAL* and *NINST* are proxies for investor sophistication; and *DISP* is a proxy for divergence of opinion. These variables indicate fundamental risk from some specific point of view. Our measures are available for the sample period from January 1982 through January 2002.

As in our earlier analysis, we sort our sample into quintiles (V1 to V5) for each month based on $V_f/P$ in the previous month. Stocks are also independently ranked in descending order of *AGE*, *NANAL* or *NINST* and in ascending order of *AQ* or *DISP*. For each proxy, the first 20% of stocks

[30] We run cross-sectional regressions of working capital accruals against previous, current, and future operating cash flows, and changes in cash sales and property, plants, and equipment, in each year and for each of the 48 Fama and French (1997) industries that has at least 20 firms.

[31] *NINST* and *SINST* (to be studied in Section 5.4) are coded as zero if a stock is not recorded in the Compact Disclosure database.

[32] Choosing different dispersion measures does not affect our results. For example, replacing the analyst *FY*1 *EPS* forecasts by *FY*2 forecasts provides similar results, because the *FY*1 and *FY*2 forecasts are highly correlated. Following Diether, Malloy and Scherbina (2002), stocks are assigned to the highest dispersion category if the mean forecast is zero.

are allocated into the first group, G1; the next 20% into the second group, G2; and so on. By doing so, we can be certain that fundamental risk measured by any proxy always increases from G1 to G5. For each partitioning variable, our procedure results in 25 portfolios in each month, with each portfolio consisting of stocks in the intersections of $V_f/P$ quintiles (V1 to V5) and fundamental risk-sorted groups (G1 to G5) and thus having similar $V_f/P$ and similar fundamental risk. We hold these portfolios for 36 months following the portfolio formation and compute the cumulative buy-and-hold returns for the V5–V1 portfolios (V5–V1 *RET*36) for each of the groups (G1 to G5), as well as the risk-adjusted monthly returns (*ALPHA*) by regressing the monthly V5–V1 returns on the Fama-French three factors and the momentum factor. Again, the returns on those stocks up to delisting during the holding period are included in our calculation of *RET*36 and *ALPHA*.

Panel A of Table 2 reports the average monthly estimates of *RET*36 and *ALPHA* for the V5–V1 portfolios in each of the fundamental risk groups, G1 to G5. In each column corresponding to a single measure of fundamental risk, we compute the difference in *RET*36 (or *ALPHA*) for the V5–V1 strategy between the lowest risk group (i.e., G1) and the highest risk group (i.e., G5). Our *t*-statistic is computed as the mean divided by the standard error of the monthly estimates and our *Z*-statistic is computed in a similar manner except that the rank measures of monthly estimates are used (i.e., the Wilcoxon rank-sum test). Moreover, to examine the relation across groups from G1 to G5, we compute a correlation between the group rank and the V5–V1 *RET*36 (or *ALPHA*) in the group. The significance level of this correlation is assessed similarly using the time-series estimates over the sample period. Finally, we apply the Newey and West (1987) procedure to correct for serial correlations in the variables of interest.

[Insert Table 2 here]

Our results show that for all the measures of fundamental risk, the mean V5–V1 *RET*36 (i.e., the mean arbitrage return) in the highest fundamental risk group (i.e., G5) is extremely small or sometimes even negative (for *AGE* and *DISP*), indicating that extremely high fundamental risk supresses arbitrageurs' incentives to exploit the arbitrage opportunities. The V5–V1 *RET*36 in the lowest risk group (i.e., G1) is significantly positive and is significantly greater than that in G5. The difference in V5–V1 *RET*36 between G1 and G5 is very large and highly significant at the 1% level in all cases. The differences are also economically significant. For example, the arbitrage return (i.e., V5–V1 *RET*36) is 21.08% for our sample stocks with the longest listing history, while the arbitrage return is -0.38% for our sample stocks with the shortest listing history, resulting a large difference of 21.46% between G1 and G5. The differences in arbitrage returns between G1 and G5 are similarly large for *AQ* (14.62%), *NANAL* (20.15%), *NINST* (22.43%) and *DISP* (24.74%).[33]

Furthermore, the correlations between the group rank and the V5–V1 *RET*36 in all cases are negative and statistically significant at the 1% level, except for *AQ* (prob. = 0.19).[34] We observe that V5–V1 *RET*36 exhibits an approximately monotonic decreasing pattern across groups G1 to G5 in all cases, except for *AQ*. Meanwhile, after adjusting for common risk factors, *ALPHA* exhibits a similar pattern to that of V5–V1 *RET*36, although the monotonicity and the significance level weaken for some cases (*AQ* and *NANAL*). Taken together, our results indicate that arbitrage returns to $V_f/P$ strategies are inversely correlated with fundamental risk, especially when it is measured by firm age (*AGE*), investor sophistication (*NANAL* and *NINST*) and divergence of opinion (*DISP*). The effect of earnings quality (*AQ*) is also economically significant. However, its effect is not monotonic, which might suggest that this variable captures other effects as well.[35]

In Panel B, for the sake of brevity, we report only the average monthly cross-sectional means of our measures of fundamental risk for each fundamental risk-sorted groups (G1 to G5), the average number of stocks used in the sorting, and the average number of stocks in the two extreme $V_f/P$ portfolios (V5 and V1). All our measures show substantial variation across groups G1 to G5, suggesting that our tests on the relation between $V_f/P$-based arbitrage returns and each of our measures for fundamental risk should offer reasonable power. Furthermore, our sorting produces modestly balanced bi-dimensional portfolios with a large number of stocks in each group, which suggests that the returns in each group are not biased by a few stocks. In fact, our results remain similar if we sort first on fundamental risk and then on $V_f/P$. Finally, we do not find any evidence that the returns to the V5–V1 strategies in each of the five groups (G1-G5) are driven by differences in any stock characteristic, such as size, book-to-market ratios, or past returns. For robustness, we also examine the one- and two-year buy-and-hold returns to the $V_f/P$ strategies in each group (G1 to G5). The patterns of the results remain the same (not shown).

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[33] Recall that V5–V1 *RET*36 is only 15.75% for the full sample.

[34] The estimates of *AQ* require six years of accounting data, naturally excluding a number of stocks with high fundamental risk. As a result, the insignificant correlation between the group rank and the V5–V1 *RET*36 for *AQ* does not necessarily mean that its effect on arbitrage profit is weak.

[35] Note that, in the univariate tests, it is difficult to control other types of arbitrage risk for each of G1 to G5 groups.

To summarize, we find strong evidence to demonstrate one aspect of the limits of arbitrage due to fundamental risk. We show that the arbitrage strategies based on $V_f/P$ work effectively only in stocks with low fundamental risk, whereas in stocks with extremely high fundamental risk, the mispricing could persist for up to 36 months, resulting in the poor performance of such strategies.

*5.3 Noise trader risk and $V_f/P$ portfolio strategies*

Another critical concern that arbitrageurs face is noise trader risk. This category of risk reflects the fact that arbitrageurs know that there are irrational noise traders in the market that there is always the risk that their positions may deteriorate purely because of noise traders. Our measure of expected noise trader risk is idiosyncratic stock return volatility (*IVO*), which is obtained by regressing daily returns on the CRSP value-weighted index over a one-year period ending with the previous month and then calculating the standard deviation of the residuals. A high expected *IVO*, which is not compensated in expected returns, deters arbitrage activities This is especially true for poorly diversified, risk-averse arbitrageurs who have limited capital resources, face potential margin calls or short squeeze risks, and risk involuntary liquidation due to principle-agent problems or liabilities secured by collateral. Therefore, we conjecture that $V_f/P$ strategies are profitable only with stocks with low noise trader risk measured by *IVO*. To test this hypothesis, we repeat the previous analysis based on *IVO*.

Table 3 reports the monthly averages of *RET*36 and *ALPHA* on the V5–V1 portfolios for each of the *IVO* quintiles (G1 to G5) as well as the means of *IVO* and the number of stocks, where G5 (G1) represents the group of stocks with the highest (lowest) *IVO*. In addition to results for the whole sample period, we also report results based on two subperiods: January 1982 to June 1994, and July 1994 to January 2002. Our separation of the sample period is a little arbitrary but simply due to two major observations. First, the performance of $V_f/P$ strategies after the mid-1990s has seldom been reported in the prior literature, and, according to our findings in Figure 1, the performance of these strategies has been disastrous during this later period. Second, Campbell et al. (2001) show that idiosyncratic stock return volatility has been rising, especially during the late 1990s. We are therefore curious to know whether an increase in noise trader risk has an impact on the deterioration of $V_f/P$ strategies during this period.

[Table 3 here]

Panel A shows that the mean V5–V1 *RET*36 in the highest *IVO* group (i.e., G5) is not profitable. It is –2.57% for the whole period, 6.75% for the first subperiod, and an extremely negative -17.93% for the second subperiod. However, the arbitrage returns (i.e., V5–V1 *RET*36) are significantly large for G1 stocks in all three periods. The difference in V5–V1 *RET*36 between G1 and G5 (i.e., G1–G5) and the correlations between V5–V1 *RET*36 and the group rank for G1 to G5 are statistically and economically significant. The return for G1–G5 is 18.25% ($t$ = 2.83 and $Z$ = 5.06) and the correlation is -0.22 (prob. < 0.01) for the whole period; the return for G1–G5 is 8.59% ($t$ = 1.89 and $Z$ = 3.34) and the correlation is -0.17 (prob. < 0.05) for the first subperiod; and the return for G1–G5 is 34.16% ($t$ = 2.31 and $Z$ = 3.92) and the correlation is -0.32 (prob. < 0.05) for the second subperiod. Obviously, during the second subperiod, the $V_f/P$ effect exhibits a monotonic and negative relationship with the degree of noise trader risk, which is also supported by the results on *ALPHA*. Panel B shows sufficient enough variation in *IVO* across groups G1 to G5, and the number of stocks used in constructing the $V_f/P$ portfolios is sufficiently large in each group.

Figure 2 further illustrates the average cumulative buy-and-hold returns at monthly intervals over the next 36 months after each portfolio formation month within the subperiod from July 1994 though January 2002. To construct this graph, the 25 *IVO*-$V_f/P$ portfolios formed by independent sorting are held for 36 months and a hedging strategy of buying the highest $V_f/P$ stocks (V5) and selling the lowest $V_f/P$ stocks (V1) is taken within each *IVO* quintile. This graph plots the time-series mean differences in cumulative returns between the V5 and V1 quintiles. It appears that the returns to the $V_f/P$ strategies grow stably and smoothly in low *IVO* quintiles (G1, G2 and G3), while in *IVO* quintile G4, the returns are much weaker and even negative sometimes. The strategy fails totally in the highest *IVO* quintile (i.e., G5).

[Figure 2 here]

Our evidence from Table 3 and Figure 2 reveals another aspect of the limits of arbitrage that comes from noise trader risk. The higher the expected *IVO* that arbitrageurs face, the fewer the incentives for them to exploit the arbitrage. As a result, it is easier to arbitrage the mispricing in stocks with lower noise trader risk. Our results seem to suggest that noise trader risk has gradually become a more and more serious concern to arbitrageurs. Finally, our results are very robust to different measures of stock volatility. Our conclusions remain unchanged when we use the historical volatility of residuals from the Fama-French three-factor model or from the Carhart four-factor model using 36 monthly returns or the total return volatility.

*5.4 Implementation risk and $V_f/P$ portfolio strategies*

The final concern for arbitrageurs is implementation risk. Unquestionably this category of risk is mainly associated with transaction costs and short-sale constraints. Our measures of implementation risk are: (1) *PRC* (the closing price at the end of previous month), (2) *BID-ASK* (the percentage of the bid-ask spread, defined as 2×(ask – bid)/(ask + bid), averaged over the last hour of the last trading day of each of the last 12 months), (3) *VOL* (the average monthly dollar trading volume over the last 12 months),[36] (4) *ILLIQ* (the modified Amihud (2002) liquidity measure, defined as the ratio of the daily price fluctuation percentage range to the daily dollar volume averaged over a maximum of one year as of the end of the previous month),[37, 38] (5) *SINST* (the percentage of shares owned by institutions at the end of the latest quarter), and (6) *SIZE* (the market value of equity at the end of the previous month). Note that data for *PRC*, *VOL*, *ILLIQ* and *SIZE* are all obtained from the CRSP database, which is available for the whole sample period. Data for *BID-ASK* are obtained from the TAQ database available for the period from January 1994 to January 2002, and data for *SINST* is from the Compact Disclosure database for the whole sample period. As discussed before, *PRC* and *BID-ASK* are proxies for direct transaction costs; *VOL* and *ILLIQ* are proxies for indirect transaction costs; *SINST* is a proxy for short-sale costs; and *SIZE* serves as a comprehensive measure of transaction costs.

We repeat the same analysis as described in Section 5.2 with each of the above measures for implementation risk. Specifically, we independently rank stocks in descending order of *PRC*, *VOL*, *SINST* and *SIZE*, and in ascending order of *BID-ASK* and *ILLIQ* in order to form five implementation risk-based groups (G1 to G5), where G5 (G1) represents the group of stocks with the highest (lowest) implementation costs.

[36] For NASDAQ stocks, we divide *VOL* by two because, unlike reported volumes on the NYSE and AMEX, reported volumes on NASDAQ include inter-dealer trades. Actually, a lot of literature suggests that the volume data on NASDAQ and the NYSE/AMEX have different implications due to distinct market microstructures and should be investigated separately (see, for example, Atkins and Dyl (1997) and Lo and Wang (2000)). We also exclude NASDAQ stocks when forming *VOL*-based groups and the results are similar.

[37] According to Amihud (2002), *ILLIQ* applies only to NYSE and AMEX stocks so that the average number of stocks used in the portfolio sorting is smaller (1,210 in Table 4).

[38] The daily price fluctuation range is defined as the maximum of (daily highest – daily lowest), (daily highest – last closing price), and (last closing price – daily lowest), divided by the last closing price.

Table 4 reports the results. For all the measures, the arbitrage returns for G1–G5 and the correlations are strongly significant at the 1% level. The difference in arbitrage returns between G1 and G5 is 29.11% and the correlation between arbitrage returns and the group ranks is -0.43 for *PRC* sorting. The corresponding figures are 31.14% and -0.39 for *BID-ASK* sorting, 14.66% and -0.25 for *VOL*, 16.85% and -0.32 for *ILLIQ*, 8.29% and -0.24 for *SINST*, and 20.52% and -0.35 for *SIZE*. Similarly, we find that V5–V1 *RET*36 in the highest implementation risk group (i.e., G5), measured by each of the above variables, is small or negative. The results for correlations or the patterns of V5–V1 *RET*36 indicate that the $V_f/P$ effect decreases with transaction costs or short-sale costs, consistent with our hypothesis that arbitrage is very limited for stocks with high implementation risk. Again, we observe similar but slightly weaker results based on *ALPHA*.

[Insert Table 4 here]

By comparing the different risk variables, we find that the measures of direct transaction costs such as *PRC* and *BID-ASK* exhibit the strongest negative effect on the $V_f/P$ strategies. Especially in the case of *BID-ASK*, V5–V1 *RET*36 is only significantly positive (26.52%) in the lowest *BID-ASK* group (i.e., G1). *ILLIQ* is a good measure for indirect transaction costs, but the sample size is smaller due to the exclusion of NASDAQ stocks. Not surprisingly, *VOL* exhibits a slightly ambiguous relation with V5–V1 *RET*36 (not monotonic), and *SIZE* shows a strong ability to affect V5–V1 *RET*36, consistent with our previous discussion about these measures of implementation risk.[39]

*5.5 Multivariate analysis of arbitrage risk*

In the previous sections, we employed univariate analysis and determined that the $V_f/P$ effect is cross-sectionally correlated with an extensive set of measures of arbitrage risk. We concluded that arbitrage risk inhibits the incentives for arbitrageurs to exploit mispricing and results in the poor performance of arbitrage strategies. Nevertheless, considering any single dimension is not enough to eliminate arbitrage risk. To protect arbitrage strategies from the downside risk as illustrated in Figure 1, it is necessary to consider multiple types of arbitrage risk. In fact, we drew a graph similar to Figure 1 for each of the arbitrage risk-based groups from G1 to G5, and found that the downside of the $V_f/P$ strategies, especially the big loss in late 1990s, cannot be entirely

[39] We argue that *VOL* contains information on both liquidity and differences of opinion, which signal the arbitrage risk in opposite directions, while *SIZE* has a uniform prediction regardless of the type of arbitrage risk it represents.

avoided by deleting stocks with high arbitrage risk measured by any single proxy (results not shown). Therefore, we explore multivariate analysis to determine whether the performance of arbitrage strategies can be significantly improved by fully considering various types of arbitrage risk.

Our integrated method is simple. As before, we first form $V_f/P$ quintiles (V1 to V5) for each month. Independent of the $V_f/P$ ranking, stocks are ranked in descending order of *SIZE*, *AGE*, *NANAL* and *PRC* and in ascending order of *AQ*, *DISP*, *IVO* and *ILLIQ*. When a stock falls in the top quintile of any measure of arbitrage risk (≥ 80% fractile), it receives the score of one. As a result, the highest score is eight, whereas the lowest score is zero. Those stocks with a zero score are assigned to the lowest arbitrage risk group (LRG), and those with the score of four or more are assigned to the highest arbitrage risk group (HRG). Effectively, LRG consists of stocks that contain no extremely high arbitrage risk measured by any of the above variables. On the other hand, HRG consists of stocks that contain at least four types of extremely high arbitrage risk. The intersections of $V_f/P$ quintiles (V1 to V5) and extreme arbitrage risk groups (LRG, HRG) result in ten portfolios in each month, with each portfolio having similar $V_f/P$ and overall arbitrage risk.

We exclude other measures of arbitrage risk in the stock ranking either because they are not available for the whole sample period (such as *BID-ASK*), or because they show subtle or non-monotonic effects on the $V_f/P$ strategies (such as *VOL*). In addition, we avoid using two ranking variables that contain the same proxy (for example, both *SINST* and *NANAL* proxy for investor sophistication). The use of *ILLIQ* in the stock ranking effectively excludes NASDAQ stocks from the resulting groups (LRG, HRG). If we exclude *ILLIQ* in the stock ranking, the results remain almost the same.

Table 5 reports the average monthly estimates of stock characteristics and cumulative buy-and-hold returns over one, two and three years (*RET*12, *RET*24 and *RET*36) for each of the stock-ranking ten portfolios. By looking across each row, we observe that the $V_f/P$ portfolios in the LRG group are composed of extremely low-risk stocks as signified by their large capitalization (*SIZE*), long history of listing (*AGE*), high earnings quality (*AQ*), high investor sophistication (*NANAL*), low divergence of opinion (*DISP*), low return volatility (*IVO*), high price (*PRC*), and high liquidity (*ILLIQ*). In contrast, the $V_f/P$ portfolios in the HRG group are in the opposite direction of arbitrage risk. The results show that $V_f/P$ has strong predictive power on cross-sectional returns in the LRG group. In particular, *RET*12, *RET*24 and *RET*36 exhibit almost a monotonic and increasing pattern across the $V_f/P$ portfolios from V1 to V5. In contrast, $V_f/P$ does not have cross-sectional predictive power for future returns in the HRG group, as indicated by a non-monotonic relation in the wrong direction.

[Table 5 here]

To allow us to take a close look at the returns on the V1, V5 and V5–V1 portfolios in the above lowest arbitrage risk group, Table 6 reports the cumulative buy-and-hold returns over one-, two- and three-year horizons (*RET*12, *RET*24 and *RET*36) year by year. For brevity, we report only the returns on portfolios formed each January from 1982 to 2002. Again, it appears that the longer we hold, the more likely we earn significantly more positive returns by using the $V_f/P$ strategies. For instance, with a three-year holding period, V5 outperforms V1 in 19 out of 21 years.

[Insert Table 6 here]

Figure 3 plots *RET*36 on the V5–V1 portfolios (V5–V1 *RET*36) for the two extreme arbitrage risk-based groups (LRG and HRG). It is clear that V5–V1 *RET*36 in the LRG group has much lower volatility and much larger returns compared with that in the HRG group. The $V_f/P$ strategy in the LRG (HRG) group earns a 36-month buy-and-hold return of 30.24% (-6.89%). More impressively, only in 16 out of 241 portfolio formation months (prob. < 7%) is the V5–V1 *RET*36 in the LRG group slightly negative, further indicating that the $V_f/P$ strategy performs substantially better when various types of arbitrage risk are taken into consideration together.

[Insert Figure 3 here]

*5.6 Regression tests*

By providing compelling evidence at the portfolio level, we highlight the important role played by various types of arbitrage risk in deterring arbitrage activities. However, it is possible that any measure presumed to represent one type of arbitrage risk in our analysis also captures the effect of other types of arbitrage risk. Since we are also interested in determining the incremental role of arbitrage risk in the $V_f/P$ effect, we perform the following multiple regression tests at the individual stock level:

$$RET36 = a + b_1 BETA + b_2 Ln(SIZE) + b_3 BTMV + b_4 RET_{-6:-1} + b_5 V_f / P$$

$$+\sum_j (c_j AR_j + d_j V_f / P \times AR_j) + e\,, \qquad (2)$$

where $AR_j$ denotes the *j-th* measure of arbitrage risk. The coefficient, $d_j$, on the interaction term in Model (2) captures how the $V_f/P$ effect varies cross-sectionally with the *j-th* measure of arbitrage risk. All measures of arbitrage risk are also included by themselves to capture their main effects on future returns. Otherwise, the coefficient, $d_j$, could be biased. We include *BETA*, *SIZE*, *BTMV* and $RET_{-6:-1}$ as the control variables to capture the systematic risk as well as other standard cross-sectional effects, such as the size and value effects documented by Fama and French (1992) and the momentum effect documented by Jegadeesh and Titman (1993).

To be included in Model (2), we require a measure of arbitrage risk to satisfy the following principles: (1) it is available for the whole sample period; (2) it has significant effect on the $V_f/P$ strategies; (3) it is not extremely correlated with the control variables; and (4) if two variables contain the same indication of a particular type of arbitrage risk, the one that shows a stronger and less ambiguous effect is chosen. As a result, we study six variables, *AGE*, *AQ*, *NANAL*, *DISP*, *IVO* and *PRC*, in our regression analysis (*SIZE* is already a control variable). In fact, all of them are used in the multiple sorting in the previous section. We do not report the result on *ILLIQ* in our regression because of two reasons. First, *ILLIQ* is highly correlated with *SIZE* (correlation = 0.82) and thus induces severe multicollinearity problems. Second, since *ILLIQ* does not apply to NASDAQ stocks, the regression results might be biased.

As a precursor to our regressions, we take a brief glance at the Spearman correlation matrix reported in Table 7. The correlations among our measures of fundamental risk, noise trader risk and implementation risk range from 0.037 to 0.650. While all these magnitudes are significantly less than one, they are all significantly different from zero at the 1% level. This suggests that in order to understand the effects of various types of arbitrage risk on the ability of $V_f/P$ to predict returns, it is not sufficient to examine the effect of only a single measure. Thus, when performing univariate analysis in the previous sections, caution is warranted in drawing conclusions about which specific type of arbitrage risk contributes most to the existence of the $V_f/P$ effect. Furthermore, even in multivariate analysis, we should be careful in drawing conclusions due to potential multicollinearity problems. However, given that most correlations are less than 0.5, it seems safe for us to perform Fama and Macbeth (1973) regressions.

[Table 7 here]

We employ the standard Fama and Macbeth (1973) method to estimate Model (2) in each month and report the means of the monthly estimates. We also report the *t*-statistics of the mean of the monthly slope estimates using the Newey and West (1987) corrected standard errors. For variables with large positive skewness, we use the logarithm transformation to normalize them.[40]

Table 8 reports the coefficient estimates based on different versions of the regression derived from Model (2). The first column (1) presents the results of a model with only the control variables and $V_f/P$. All the slope coefficients except that on *SIZE* are significant at the 1% level with the expected signs. These results indicate the presence of the value, momentum and value-to-price effects and the disappearance of the size effect, which is consistent with the prior literature. Columns (2) to (7) present the results of the models in which each of our six measures of arbitrage risk together with the interaction term is added one at a time. Each of the interaction terms in the columns has a significant slope coefficient with the expected sign. The coefficient on $V_f/P \times Ln(AGE)$ is 0.036 with a t-value of 4.00. The coefficient on $V_f/P \times AQ$ is –1.157 with a *t*-value of –4.00. The coefficient on $V_f/P \times NANAL$ is 0.001 with a *t*-value of 2.13. The coefficients on $V_f/P \times Ln(1+DISP)$, $V_f/P \times IVO$, and $V_f/P \times Ln(PRC)$ are –0.134, –0.017, and 0.017 with *t*-values of –4.75, –2.62, and 2.12, respectively. These results suggest that the $V_f/P$ effect decreases with an increase in arbitrage risk measured by each of our measures, consistent with our univariate portfolio analysis reported in Tables 2, 3 and 4.

[Table 8 here]

Column (8) presents the results of a model with five measures of arbitrage risk except *AQ*, and Column (9) presents the complete model. Given that the calculation of *AQ* requires accounting data for six years, the exclusion of *AQ* in the regression results in a much lager sample (average stock number of 1,635 in Column (8) versus 948 in Column (9)). In Column (8), the interaction term, $V_f/P \times Ln(AGE)$, remains positive and significant with a coefficient of 0.018 and a *t*-value of 2.10 and $V_f/P \times Ln(1+DISP)$ remains negative and significant with a coefficient of –0.108 and a *t*-value of –3.84. This indicates that firm age and divergence of opinion incrementally explain the cross-sectional variation in the $V_f/P$ effect beyond the other types of risk. However, in Column (9), the significance of the coefficient on $V_f/P \times Ln(AGE)$ disappears, while the coefficient on $V_f/P \times Ln(1+DISP)$ remains negative and significant. The coefficient on $V_f/P \times AQ$ is negative and significant with a *t*-value of –2.39. The result suggests that when the sample is restricted to a smaller set of stocks caused by the availability of *AQ*, the incremental

[40] *DISP* can be zero, so we use *Ln*(1+*DISP*) instead of *Ln*(*DISP*).

effect of firm age is hidden, and earnings quality and divergence of opinion exert an incremental explanatory power on the $V_f/P$ effect. Finally, all other interaction terms in Columns (8) and (9) are insignificant. A likely explanation is that the associated measures of arbitrage risk are correlated with each other and some variables can subsume the similar underling effects of others. The results in Table 8 suggest that among three types of arbitrage risk, fundamental risk is more important than other two types of arbitrage risk.

## 6. Conclusion

Using various measures of arbitrage risk identified in the literature, we find that the ability of the fundamental value-to-price ($V_f/P$) ratio to predict long-term future returns is extremely weak for stocks with the highest arbitrage risk measured by their short listing history, low earnings quality, low investor sophistication, great divergence of opinion, high return volatility, or high transaction costs. As the $V_f/P$ effect is widely accepted to be due to the correction of market mispricing by rational arbitrageurs, our results are consistent with the view from behavioral finance, highlighting the importance of arbitrage risk in undermining the efficiency of the pricing mechanism. We also find that when considering multiple types of arbitrage risk together, the ability of $V_f/P$ to predict future cross-sectional returns is significantly more stable with a larger magnitude. Specifically, in the group of stocks with no measures of arbitrage risk falling in the worst quintile (LRG: about 20% of the stocks in our sample), the hedging strategy that longs in the highest $V_f/P$-quintile and shorts in the lowest $V_f/P$-quintile earns a 36-month buy-and-hold return of 30.24%. In contrast, the corresponding return in the group of stocks with four or more measures of arbitrage risk falling in the worst quintile (HRG: about 14% of the stocks in our sample) is a negative of -6.89%. Besides, the $V_f/P$ strategy in the LRG group exhibits negative returns in only 16 out of 241 portfolio formation months. Furthermore, our results show that firm age, earnings quality, as well as divergence of opinion have incremental power beyond other measures of risk in explaining the cross-sectional variation in the $V_f/P$ effect. This finding suggests that these arbitrage risks deter arbitrage activities and are not easily mitigated as time goes by when implementing $V_f/P$ strategies. To the best of our knowledge, our paper is among the first to examine the effects of various types of arbitrage risk on long-term arbitrage returns coming from price convergence in a large sample.

It is useful to put our results into perspective with the results in the recent literature. In an interesting paper using a similar research method, Ali, Hwang and Trombley (2003b) demonstrate that the long-term book-to-market (BTMV) effect is greater for stocks with higher arbitrage risk measured by higher idiosyncratic volatility, higher transaction costs, and lower investor sophistication. They further argue that their results are consistent with the market mispricing explanation for the BTMV effect, which seems contradictory to our results. In their analysis, however, they posit that the returns to the BTMV strategies are due to mispricing. We argue that the validity of this argument remains questionable because the risk-based explanation also supports their results (see, for example, Fama and French (1993)). Thus, our results differ fundamentally from theirs in that the returns to the $V_f/P$ strategies in our analysis are explicitly due to the convergence of mispricing, whereas the returns to the BTMV strategies are more likely due to the widening of mispricing if their argument is correct. Furthermore, some recent papers (see Francis et al. (2003), Jiang et al. (2005), and Zhang (2006)) document that certain return anomalies are stronger among stocks with higher information uncertainty, a parallel concept to our concept of arbitrage risk. However, our results do not contradict the results in these papers, because we focus on long-term arbitrage returns driven by the activities of rational arbitrageurs, whereas they emphasize short-term returns driven by particular investor behavioral biases.

Although our measures of arbitrage risk are motivated by the prior literature, we recognize the limitation of our study in differentiating the effect of various types of arbitrage risk. Since none of our measures is a pure measure and they are correlated with each other, it is very difficult to determine the exact channel through which arbitrage risk arising from any specific measure affects arbitrage returns. For example, our finding that the $V_f/P$ effect is weaker for stocks from smaller size firms could be also related to transaction costs, fundamental uncertainty, or investor sophistication. We leave such issues for future research. The primary message of this paper is that in real financial markets, arbitrage risk does erode arbitrage returns economically. Hence, arbitrageurs take various types of arbitrage risk into account before they exploit arbitrage opportunities.

## References

Ali, Ashiq, Lee-Seok Hwang, and Mark A. Trombley, 2003a, Residual-income-based valuation predicts future stock returns: evidence on mispricing vs. risk explanations, *Accounting Review* 78, 377-396.

Ali, Ashiq, Lee-Seok Hwang, and Mark A. Trombley, 2003b, Arbitrage risk and the book-to-market anomaly, *Journal of Financial Economics* 69, 355-373.

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

Amihud, Yakov, and Haim Mendelson, 1986, Asset pricing and the bid–ask spread, *Journal of Financial Economics* 17, 223–249.

Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short interest, institutional ownership, and stock returns, *Journal of Financial Economics*, 78, 243–276.

Atkins, Allen B., and Edward A. Dyl, 1997, Transactions costs and holding periods for common stocks, *Journal of Finance* 52, 309–325.

Baker, Malcolm, and Serkan Savasoglu, 2002, Limited arbitrage in mergers and acquisitions, *Journal of Financial Economics* 64, 91-115.

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can investors profit from the prophets? Security analyst recommendations and stock returns, *Journal of Finance* 56, 531–563.

Barberis, Nicholas, and Richard Thaler, 2003, A survey of behavior finance, in George Constantinides, Milton Harris, and Ren´e Stulz, eds.: *Handbook of the Economics of Finance* (North-Holland, Boston).

Basak, Suleyman, and Benjamin Croitoru, 2000, Equilibrium mispricing in a capital market with portfolio constraints, *Review of Financial Studies* 13, 715-748.

Brennan, Michael, Narasimhan Jagadeesh, and Bhaskaran Swaminathan, 1993, Investment analysis and the adjustment of stock prices to common information, *Review of Financial Studies* 6, 799–824.

Brennan, Michael, and Avanidhar Subrahmanyam, 1995, Investment analysis and price formation in securities markets, *Journal of Financial Economics* 38, 361-381.

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, *Journal of Finance* 56, 1-43.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chalmers, John M. R., and Gregory B. Kadlec, 1998, An empirical examination of the amortized spread, *Journal of Financial Economics* 48, 159-188.

Chen, Joseph, Harrison Hong, and Jeremy C. Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics* 66, 171–205.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2001, Market liquidity and trading activity, *Journal of Finance* 56, 501-530.

Chordia, Tarun, Avanidhar Subrahmanyam, and V. Ravi Anshuman, 2001, Trading activity and expected stock returns, *Journal of Financial Economics* 59, 3-32.

Datar, Vinay, Narayan Naik, and Robert Radcliffe, 1998, Liquidity and asset returns: an alternative test, *Journal of Financial Markets* 1, 203-220.

D'Avolio, Gene, 2002, The market for borrowing stock, *Journal of Financial Economics* 66, 271-306.

Dechow, Patricia M., and Ilia D. Dichev, 2002, The quality of accruals and earnings: the role of accrual estimation errors, *The Accounting Review* 77 (Supplement), 35-59.

Dechow, Patricia M., Amy P. Hutton, Lisa Meulbroek, and Richard G. Sloan, 2001, Short-sellers, fundamental analysis and stock returns, *Journal of Financial Economics* 61, 77–106.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703-738.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1991, The survival of noise traders in financial markets, *Journal of Business* 64, 1-19.

Diether, Karl. B., Christopher J. Malloy, and Anna Scherbina, 2002, Difference of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113-2141.

Edwards, Edgar O., and Philip W. Bell, 1961, *The Theory and Measurement of Business Income* (University of California Press, Berkeley).

Fama, Eugene F. and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

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

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return and equilibrium: empirical tests, *Journal of Political Economy* 81, 607–636.

Feltham, Gerald A., and James A. Ohlson, 1995, Valuation and clean surplus accounting for operating and financial activities, *Contemporary Accounting Research* 11, 689-731.

Frankel, Richard, and Charles M.C. Lee, 1998, Accounting valuation, market expectation, and cross-sectional stock returns, *Journal of Accounting and Economics* 9, 195-228.

Francis, Jennifer, Ryan LaFond, Per Olsson, and Katherine Schipper, 2003, Accounting anomalies and information uncertainty, working paper, Duke University, Wisconsin University, and the Financial Accounting Standards Board.

Geczy, Christopher C., David K. Musto, and Adam V. Reed, 2002, Stocks are special too: an analysis of the equity lending market, *Journal of Financial Economics* 66, 241–269.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265–295.

Hong, Harrison, and Jeremy C. Stein, 2003, Differences of opinion, short-sales constraints and market crashes, *Review of Financial Studies* 16, 487-525.

Jiang, Guohua, Charles M.C. Lee, and Yi Zhang, 2005, Information uncertainty and expected returns, *Review of Accounting Studies* 10, No. 2/3.

Jorion, Philippe, 1997, Lessons from the orange county bankruptcy, *Journal of Derivatives* Summer 1997, 61-66.

Keim, Donald B., and Ananth Madhavan, 1996, The upstairs market for large-block transactions: analysis and measurement of price effects, *Review of Financial Studies* 9, 1–36.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian investment, extrapolation and risk, *Journal of Finance* 49, 1541–1578.

Lamont Owen A., and Richard H. Thaler, 2004, Can the market add and subtract? Mispricing in tech stock carve-outs, *Journal of Political Economy* 111, 227−268.

Lee, Charles M.C., and Bhaskaran Swaminathan, 2000, Price momentum and trading volume, *Journal of Finance* 55, 2017–2069.

Lesmond, David A., Michael J. Schill, and Chunsheng Zhou, 2004, The illusory nature of momentum profits, *Journal of Financial Economics* 71, 349–380.

Liu, Jun, and Francis Longstaff, 2004, Losing money on arbitrages: optimal dynamic portfolio choice in markets with arbitrage opportunities, *Review of Financial Studies* 17, 611–641.

Lo, Andrew W., and Jiang Wang, 2000, Trading volume: definitions, data analysis, and implications of portfolio theory, *Review of Financial Studies* 13, 257-300.

Loewenstein, Mark, and Gregory A. Willard, 2000, Rational equilibrium asset-pricing bubbles in continuous trading models, *Journal of Economic Theory* 91, 17-58.

Lowenstein, Roger, 2001, *When Genius Failed: The Rise and Fall of Long-Term Capital Management*, Fourth Estate.

Miller, Merton H., and David J. Ross, 1997, The orange county bankruptcy and its aftermath: some new evidence, *Journal of Derivatives* Summer 1997, 51-60.

Mitchell, Mark, Todd Pulvino, and Erik Stafford, 2002, Limited arbitrage in equity markets, *Journal of Finance* 57, 551−584.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics*, 78, 277−309.

Newey, Whitney, and Kenneth West, 1987, A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Ofek, Eli, and Matthew Richardson, 2002, DotCom mania: The rise and fall of Internet stocks, *Journal of Finance* 58, 1113-1138.

Ohlson, James A., 1990, A synthesis of security valuation theory and the role of dividends, cash flows, and earnings, *Contemporary Accounting Research* 6, 648-676.

Ohlson, James A., 1995, Earnings, book values, and dividends in security valuation, *Contemporary Accounting Research* 11, 661-687.

Pontiff, Jeffrey, 1996, Costly arbitrage: evidence from closed end funds, *Quarterly Journal of Economics* 111, 1135–1152.

Shleifer, Andrei, Robert Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35–55.

Warther, Vincent A., 1995, Aggregate mutual fund flows and security returns, *Journal of Financial Economics* 39, 209–235.

Xie, Shibin, 2004, The convergence of prices to fundamental values, working paper, University of Iowa.

Zhang, X. Frank, 2006, Information uncertainty and stock returns, *Journal of Finance* 61, 105–136.

**Table 1**
**Descriptive statistics for $V_f/P$ quintile portfolios**

This table presents the characteristics of quintile portfolios formed each month from January 1982 to December 2004 based on the value-to-price ratio ($V_f/P$) in the previous month. Panel A reports the time-series averages of cross-sectional means of firm characteristics. $V_f/P$ is the analyst-based EBO fundamental value divided by the closing stock price in the previous month. *SIZE* is the market value of equity at the end of the previous month. *BTMV* is the book-to-market ratio, where the book value from July of year *t* to June of year *t*+1 is the book value of equity at the end of the fiscal year ending in calendar year *t*–1 and the market value of equity is calculated as the price multiplied by the number of shares outstanding at the end of December of year *t*–1. *PRC* is the stock price at the end of the previous month. $RET_{-6:-1}$ is the cumulative return over the past six months as of the end of the previous month. N is the average number of stocks in each quintile portfolio. Panel B reports the post-ranking characteristics for equally weighted portfolios with different holding periods after portfolio formation. $RET_{1:n}$ is the average buy-and-hold return of the equally weighted portfolio with a holding period of *n* months after formation. *BETA* is the time-series average of the mean systematic risk of stocks in each portfolio, estimated using monthly returns over a 36-month period beginning from the current month. *ALPHA* is the risk-adjusted return of each portfolio with a holding period of only one month, estimated as the intercept by regressing the monthly portfolio excess returns on the Fama-French three factors and the momentum factor. Stocks with prices of less than five dollars are excluded from our sample. Statistical significance is reported for the difference in values between portfolio V5 and portfolio V1 (denoted as V5 – V1 Diff). The *t*-statistic is computed as the mean divided by the standard error of the monthly values of the variable. The Newey and West (1987) procedure is used to adjust for serial correlations. $^{***}$, $^{**}$ and $^{*}$ indicate significance levels of 1%, 5% and 10% (two-tailed), respectively.

| | $V_f/P$ Quintile | | | | | | |
|---|---|---|---|---|---|---|---|
| | V1 (Lowest) | V2 | V3 | V4 | V5 (Highest) | All firms | V5 – V1 Diff |
| *Panel A: Firm characteristics when quintile portfolios are formed* | | | | | | | |
| $V_f/P$ | 0.28 | 0.68 | 0.87 | 1.12 | 2.11 | 1.01 | $1.83^{***}$ |
| *SIZE* (billion $) | 2.06 | 2.47 | 2.33 | 1.89 | 2.01 | 2.15 | -0.05 |
| *BTMV* | 0.69 | 0.65 | 0.71 | 0.78 | 0.72 | 0.71 | $0.04^{*}$ |
| *PRC*($) | 24.90 | 28.91 | 27.57 | 25.22 | 22.63 | 25.84 | $-2.27^{**}$ |
| $RET_{-6:-1}$ (%) | 17.69 | 14.31 | 10.60 | 7.18 | 2.16 | 10.39 | $-15.53^{***}$ |
| Number of stocks | 441 | 441 | 441 | 441 | 441 | 2,206 | |
| *Panel B: Post-ranking return characteristics with different holding periods* | | | | | | | |
| *BETA* | 1.31 | 1.05 | 0.97 | 0.93 | 1.03 | 1.06 | $-0.29^{***}$ |
| *ALPHA* (%) | -0.35 | -0.11 | 0.10 | 0.29 | 0.36 | -- | $0.72^{***}$ |
| $RET_{1:1}$ (%) | 0.83 | 1.17 | 1.41 | 1.62 | 1.61 | 1.33 | $0.78^{***}$ |
| $RET_{1:3}$ (%) | 3.24 | 3.95 | 4.44 | 4.76 | 4.50 | 4.18 | $1.27^{**}$ |
| $RET_{1:6}$ (%) | 6.81 | 8.06 | 9.06 | 9.47 | 8.67 | 8.42 | $1.86^{*}$ |
| $RET_{1:9}$ (%) | 10.02 | 12.14 | 13.56 | 13.99 | 12.91 | 12.52 | $2.89^{**}$ |
| $RET_{1:12}$ (%) | 12.92 | 15.96 | 17.79 | 18.29 | 17.15 | 16.42 | $4.23^{***}$ |
| $RET_{1:24}$ (%) | 24.27 | 31.04 | 35.54 | 36.17 | 34.39 | 32.28 | $10.12^{***}$ |
| $RET_{1:36}$ (%) | 41.82 | 51.33 | 58.51 | 58.47 | 57.57 | 53.54 | $15.75^{***}$ |

**Table 2**
**Portfolio returns to V5–V1 strategies, across quintiles of firm age, earnings quality, investor sophistication and divergence of opinion**

Panel A of this table presents the time-series averages of the 36-month buy-and-hold returns (*RET*36, in %) and risk-adjusted monthly returns (*ALPHA*, in %) to a hedging strategy of buying the highest $V_f/P$ stocks and selling the lowest $V_f/P$ stocks within quintiles ranked by a particular measure of fundamental risk. $V_f/P$ is the analyst-based EBO fundamental value divided by the closing stock price in the previous month. *AGE* is defined as the number of months between event month *t* and the first month that a stock appears in CRSP. *AQ* is the standard deviation of the residuals from cross-sectional regressions relating accruals to cash flows over year *t*-5 to year *t*-1. *NANAL* is the number of analysts following a stock in the previous month included in I/B/E/S. *NINST* is the number of institutional investors at the end of the latest quarter recorded in the Compact Disclosure database, and is treated as zero if the firm is not included. *DISP* is the dispersion in analysts' earnings forecasts in the previous month, defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts to the absolute value of the mean forecast reported in the I/B/E/S Summary History file. Each month stocks are assigned to quintiles (V1 to V5) based on the magnitude of $V_f/P$ in the previous month. Stocks are also independently assigned to quintiles (G1 to G5) by their rankings based on *AGE*, *AQ*, *NANAL*, *NINST* or *DISP*. Stocks are ranked in descending order for *AGE*, *NANAL*, and *NINST*, and in ascending order for *AQ* and *DISP*. Stocks with prices of less than five dollars are excluded from our sample. Portfolios are held for 36 months and portfolio returns are equally weighted. *RET*36 is the 36-month buy-and-hold return differential after the portfolio formation between the highest $V_f/P$-portfolio and the lowest $V_f/P$-portfolio (V5–V1). *ALPHA* is the corresponding risk-adjusted return, estimated as the intercept by regressing the monthly V5–V1 returns on the Fama-French three factors and the momentum factor. G1–G5 represents the difference in *RET*36 (or *ALPHA*) between quintile G1 and quintile G5. Correlation is the across-quintile correlation between quintile ranks (i.e., 1 to 5) and *RET*36 (or *ALPHA*) of the quintiles. Statistical significance is reported for G1–G5 and correlations. The *t*-statistic is computed as the time-series mean divided by the standard error of the monthly estimates and the *Z*-statistic is computed similarly except that the rank measures of monthly estimates are used in the Wilcoxon rank-sum test. The Newey and West (1987) procedure is used to adjust for serial correlations in returns induced by overlapping holding periods. Panel B presents the time-series averages of cross-sectional means of variables within each of the quintile groups (G1 to G5) as well as the average number of stocks. N represents the total number of stocks used in the portfolio sorting, and the left and right numbers in parentheses represent the number of stocks in the highest $V_f/P$-portfolio and the lowest $V_f/P$-portfolio within each of the quintiles (G1 to G5), respectively. The portfolio formation period ranges from January 1982 through January 2002. $^{***}$, $^{**}$ and $^{*}$ indicate significance levels of 1%, 5% and 10% (two-tailed), respectively.

**Table 2 (continued)**

| Information | Firm age | | Earnings quality | | Investor sophistication | | | | Divergence of opinion | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | *AGE* (months) | | *AQ* (%) | | *NANAL* | | *NINST* | | DISP ($10^{-1}$) | |
| *Panel A: 36-month buy-and-hold returns and risk-adjusted monthly returns* | | | | | | | | | | |
| | *RET36* | *ALPHA* | *RET36* | *ALPHA* | *RET36* | *ALPHA* | *RET36* | *ALPHA* | *RET36* | *ALPHA* |
| G1 | 21.08 | 0.11 | 21.44 | 0.09 | 27.54 | 0.05 | 27.89 | 0.13 | 24.20 | 0.10 |
| G2 | 20.58 | 0.04 | 23.30 | 0.07 | 17.54 | -0.07 | 19.30 | -0.11 | 21.08 | -0.08 |
| G3 | 20.10 | 0.05 | 26.66 | 0.15 | 12.29 | -0.14 | 13.20 | -0.11 | 20.68 | -0.07 |
| G4 | 10.95 | -0.08 | 22.64 | 0.15 | 12.51 | 0.00 | 6.31 | -0.10 | 16.91 | -0.05 |
| G5 | -0.38 | -0.36 | 6.82 | -0.10 | 7.39 | -0.08 | 5.46 | -0.13 | -0.54 | -0.23 |
| G1 – G5 | 21.46*** | 0.47*** | 14.62*** | 0.20** | 20.15*** | 0.13 | 22.43*** | 0.27*** | 24.74*** | 0.33*** |
| (*t*-statistic) | (3.53) | (4.31) | (2.66) | (2.23) | (5.91) | (1.59) | (6.76) | (3.84) | (7.03) | (6.48) |
| *Z*-statistic | 6.15*** | 6.49*** | 3.51*** | 3.36*** | 8.74*** | 2.70*** | 9.61*** | 5.89*** | 9.54*** | 8.16*** |
| Correlation | -0.25*** | -0.21*** | -0.08 | -0.07 | -0.33*** | -0.08 | -0.40*** | -0.19*** | -0.35*** | -0.23*** |
| (*p*-value) | (0.00) | (0.00) | (0.19) | (0.29) | (0.00) | (0.21) | (0.00) | (0.00) | (0.00) | (0.00) |
| *Panel B: Mean of variables and number of stocks* | | | | | | | | | | |
| N | 2,175 | | 1,192 | | 2,175 | | 2,175 | | 1,973 | |
| G1 | 547.79 | | 0.93 | | 22.28 | | 254.55 | | 0.13 | |
| (V5, V1) | (88, 60) | | (43, 31) | | (82, 77) | | (83, 69) | | (78, 52) | |
| G2 | 258.03 | | 1.94 | | 11.49 | | 94.60 | | 0.28 | |
| (V5, V1) | (77, 81) | | (43, 50) | | (70, 87) | | (71, 87) | | (77, 50) | |
| G3 | 158.73 | | 2.88 | | 6.65 | | 51.57 | | 0.49 | |
| (V5, V1) | (85, 85) | | (44, 49) | | (82, 84) | | (77, 95) | | (85, 54) | |
| G4 | 90.33 | | 4.24 | | 3.79 | | 28.57 | | 0.94 | |
| (V5, V1) | (88, 100) | | (49, 52) | | (92, 85) | | (95, 91) | | (89, 74) | |
| G5 | 41.53 | | 8.05 | | 1.60 | | 12.07 | | 6.61 | |
| (V5, V1) | (97, 109) | | (59, 56) | | (109, 102) | | (108, 93) | | (65, 165) | |

**Table 3**
**Portfolio returns to V5–V1 strategies, across quintiles of idiosyncratic stock volatility (IVO)**

Panel A of this table presents the time-series averages of 36-month buy-and-hold returns (*RET*36, in %) and risk-adjusted monthly returns (*ALPHA*, in %) to a hedging strategy of buying the highest $V_f/P$ stocks and selling the lowest $V_f/P$ stocks within quintiles of idiosyncratic stock volatility (*IVO*, in %). *IVO* is obtained by regressing daily returns on the CRSP value-weighted index over a one-year period ending with the previous month and then calculating the standard deviation of the residuals. The portfolio formation procedures and the definitions of additional variables are described in Table 2. The portfolio formation period ranges from January 1982 through January 2002 and is separated into two subperiods: January 1982 to June 1994 and July 1994 to January 2002. $^{***}$, $^{**}$ and $^{*}$ indicate significance levels of 1%, 5% and 10% (two-tailed), respectively.

| | Whole time period | | Subperiod | | Subperiod | |
|---|---|---|---|---|---|---|
| IVO Quintile | 1982:01 - 2002:01 | | 1982:01 - 1994:06 | | 1994:07 – 2002:01 | |
| *Panel A: 36-month buy-and-hold returns and risk-adjusted monthly returns* | | | | | | |
| | *RET*36 | *ALPHA* | *RET*36 | *ALPHA* | *RET*36 | *ALPHA* |
| G1: Lowest | 15.68 | -0.06 | 15.34 | -0.09 | 16.23 | -0.01 |
| G2 | 21.34 | 0.07 | 25.19 | 0.15 | 14.99 | -0.07 |
| G3 | 18.18 | 0.04 | 21.57 | 0.18 | 12.59 | -0.19 |
| G4 | 11.66 | -0.07 | 18.14 | 0.16 | 1.00 | -0.45 |
| G5: Highest | -2.57 | -0.26 | 6.75 | 0.11 | -17.93 | -0.87 |
| G1 – G5 | 18.25$^{***}$ | 0.20$^{*}$ | 8.59$^{*}$ | -0.20$^{***}$ | 34.16$^{**}$ | 0.86$^{***}$ |
| *t*-statistic | (2.83) | (1.74) | (1.89) | (-2.88) | (2.31) | (4.03) |
| *Z*-statistic | 5.06$^{***}$ | 1.39 | 3.34$^{***}$ | -4.49$^{***}$ | 3.92$^{***}$ | 5.94$^{***}$ |
| Correlation | -0.22$^{***}$ | -0.03 | -0.17$^{**}$ | 0.18$^{*}$ | -0.32$^{**}$ | -0.37$^{***}$ |
| *p*-value | (0.00) | (0.64) | (0.03) | (0.06) | (0.02) | (0.00) |
| *Panel B: Mean of IVO and number of stocks* | | | | | | |
| N | 2175 | | 1806 | | 2783 | |
| G1: Lowest | 1.27 | | 1.16 | | 1.46 | |
| (V5, V1) | (72, 47) | | (71, 36) | | (73, 64) | |
| G2 | 1.79 | | 1.63 | | 2.05 | |
| (V5, V1) | (70, 69) | | (59, 63) | | (89, 80) | |
| G3 | 2.29 | | 2.06 | | 2.67 | |
| (V5, V1) | (83, 82) | | (62, 72) | | (118, 98) | |
| G4 | 2.95 | | 2.62 | | 3.51 | |
| (V5, V1) | (102, 96) | | (75, 84) | | (147, 116) | |
| G5: Highest | 4.19 | | 3.68 | | 5.04 | |
| | (108, 140) | | (94, 105) | | (130, 198) | |

**Table 4**
**Portfolio returns to V5–V1 strategies, across quintiles of transaction costs, liquidity and short-sale constraints**

Panel A of this table presents the time-series averages of 36-month buy-and-hold returns (*RET*36, in %) and risk-adjusted monthly returns (*ALPHA*, in %) to a hedging strategy of buying the highest $V_f/P$ stocks and selling the lowest $V_f/P$ stocks within quintiles of a particular measure of implementation risk. *PRC* is the closing stock price in the previous month. *BID-ASK* is the percentage of the bid-ask spread, defined as 2×(ask – bid)/(bid + ask), averaged over the last hour of the last trading day of each of the last 12 months. *VOL* is the average monthly dollar trading volume over the last 12 months. *ILLIQ* is the ratio of the daily price percentage fluctuation to the daily dollar volume averaged over a maximum of one year at the end of the previous month. *SINST* is the percentage of shares owned by institutions at the end of the latest quarter recorded in the Compact Disclosure database, and is treated as zero if the firm is not included. *SIZE* is the market value of equity at the end of the previous month. The portfolio formation procedures and the definitions of additional variables are described in Table 2. The portfolio formation period ranges from January 1982 to January 2002, expect for *BID-ASK* for which the portfolio formation period ranges from January 1994 to January 2002. $^{***}$, $^{**}$ and $^{*}$ indicate significance levels of 1%, 5% and 10% (two-tailed), respectively.

**Table 4 (continued)**

| Variable | *PRC* ($) | | *BID-ASK* (%) | | *VOL* ($ million) | | *ILLIQ* ($10^{-7}$) | | *SINST* (%) | | *SIZE* ($ billion) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: 36-month buy-and-hold returns and risk-adjusted monthly returns* | | | | | | | | | | | | |
| | RET36 | ALPHA | RET36 | ALPHA | RET36 | ALPHA | RET36 | ALPHA | RET36 | ALPHA | RET36 | ALPHA |
| G1 | 25.65 | 0.00 | 26.52 | -0.16 | 25.20 | 0.02 | 18.14 | 0.05 | 21.78 | -0.01 | 22.41 | 0.00 |
| G2 | 21.56 | 0.03 | 0.58 | -0.44 | 16.79 | -0.05 | 28.05 | 0.22 | 18.46 | -0.02 | 24.74 | 0.00 |
| G3 | 20.47 | 0.03 | -2.65 | -0.42 | 2.21 | -0.16 | 16.82 | 0.05 | 16.57 | -0.08 | 10.80 | -0.10 |
| G4 | 9.54 | -0.16 | -10.09 | -0.56 | 5.49 | -0.09 | 10.98 | -0.07 | 9.47 | -0.15 | 6.67 | -0.10 |
| G5 | -3.47 | -0.24 | -4.62 | -0.35 | 10.55 | -0.04 | 1.30 | -0.11 | 13.50 | -0.01 | 1.89 | -0.18 |
| G1 – G5 | 29.11*** | 0.24*** | 31.14*** | 0.19* | 14.66*** | 0.06 | 16.85*** | 0.16** | 8.29*** | 0.00 | 20.52*** | 0.19** |
| (*t*-statistic) | 6.59 | 3.14 | 4.76 | 1.81 | 3.83 | 0.77 | 4.85 | 2.29 | 3.01 | 0.12 | 5.05 | 2.55 |
| *Z*-statistic | 9.94*** | 5.13*** | 6.53*** | 2.60*** | 6.01*** | 1.17 | 7.38*** | 4.26*** | 5.44*** | 0.08 | 8.03*** | 4.26*** |
| Correlation | -0.43*** | -0.21*** | -0.39*** | -0.17** | -0.25*** | -0.04 | -0.32*** | -0.23*** | -0.24*** | -0.08* | -0.35*** | -0.18*** |
| (*p*-value) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) | (0.52) | (0.00) | (0.00) | (0.00) | (0.09) | (0.00) | (0.00) |
| *Panel B: Mean of variables and number of stocks* | | | | | | | | | | | | |
| N | 2,175 | | 2,754 | | 2,161 | | 1,210 | | 2,175 | | 2,175 | |
| G1 | 56.01 | | 0.66 | | 608.83 | | 0.03 | | 68.43 | | 8.64 | |
| (V5, V1) | (61, 94) | | (76, 129) | | (92, 80) | | (58, 40) | | (74, 82) | | (81, 76) | |
| G2 | 30.71 | | 1.15 | | 68.15 | | 0.11 | | 52.37 | | 0.98 | |
| (V5, V1) | (61, 75) | | (89, 105) | | (76, 93) | | (42, 45) | | (86, 84) | | (65, 89) | |
| G3 | 21.73 | | 1.73 | | 21.08 | | 0.35 | | 39.90 | | 0.37 | |
| (V5, V1) | (79, 74) | | (108, 108) | | (78, 94) | | (42, 50) | | (90, 85) | | (71, 92) | |
| G4 | 14.85 | | 2.64 | | 6.89 | | 1.09 | | 27.28 | | 0.16 | |
| (V5, V1) | (102, 82) | | (130, 102) | | (90, 86) | | (44, 54) | | (93, 86) | | (94, 90) | |
| G5 | 8.42 | | 4.81 | | 1.67 | | 6.97 | | 12.22 | | 0.06 | |
| (V5, V1) | (132, 110) | | (148, 106) | | (96, 79) | | (56, 54) | | (92, 97) | | (124, 87) | |

**Table 5**
**Descriptive statistics for portfolios formed on $V_f/P$ and on different measures of arbitrage risk independently**

This table presents the time-series averages of the characteristics of portfolios formed by independently sorting on the value-to-price ratio ($V_f/P$) and a particular measure of arbitrage risk. $V_f/P$ is the value-to-price ratio. *AGE* is firm age. *AQ* is earnings quality. *NANAL* is the number of analysts following a stock. *DISP* is the dispersion in analysts' forecasts. *IVO* is the idiosyncratic stock volatility. *PRC* is the stock price. *ILLIQ* is the illiquidity of a stock. The detailed definitions of these variables are given in Tables 2-4. Each month from January 1982 through January 2002 stocks are assigned into quintiles (V1 to V5) based on the magnitude of $V_f/P$ of the previous month. Stocks are also independently ranked based on *SIZE*, *AGE*, *NANAL* and *PRC* in descending order and on *AQ*, *DISP*, *IVO* and *ILLIQ* in ascending order. If a stock falls into the top quintile (≥ 80% fractile) of any of these variables, it is given the score of one for each measure of arbitrage risk. Those stocks that receive a zero score are assigned to the lowest arbitrage risk group (LRG) and those that receive the score of four or more are assigned to the highest arbitrage risk group (HRG). Stocks with prices of less than five dollars are excluded from our sample. The intersections of $V_f/P$-quintiles and LRG or HRG result in ten portfolios. Portfolios are held for 36 months and portfolio returns are equally weighted. *RET*12, *RET*24 and *RET*36 represent the cumulative buy-and-hold return over one, two and three years, respectively. N represents the average number of stocks in each portfolio. V5–V1 is the difference in value of the variable of interest between portfolio V5 and portfolio V1.

| Arbitrage Risk | $V_f/P$ quintile | *SIZE* ($ billion) | *AGE* (month) | *AQ* (%) | *NANAL* | *DISP* ($10^{-1}$) | *IVO* (%) | *PRC* ($) | *ILLIQ* ($10^{-7}$) | *RET*12 (%) | *RET*24 (%) | *RET*36 (%) | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| LRG | V1 | 6.27 | 345.68 | 2.50 | 14.46 | 0.51 | 1.86 | 42.50 | 0.34 | 12.59 | 23.01 | 36.25 | 50 |
| | V2 | 5.56 | 366.73 | 2.34 | 14.83 | 0.43 | 1.74 | 41.15 | 0.31 | 14.92 | 29.23 | 47.83 | 96 |
| | V3 | 4.21 | 383.58 | 2.17 | 14.49 | 0.44 | 1.67 | 37.79 | 0.31 | 15.79 | 32.37 | 53.98 | 101 |
| | V4 | 3.50 | 427.63 | 1.85 | 15.28 | 0.43 | 1.54 | 33.56 | 0.27 | 16.67 | 33.65 | 53.25 | 110 |
| | V5 | 5.45 | 433.41 | 2.24 | 17.34 | 0.42 | 1.70 | 36.30 | 0.20 | 19.32 | 40.85 | 66.49 | 88 |
| | V5–V1 | -0.82 | 87.74 | -0.27 | 2.88 | -0.09 | -0.16 | -6.20 | -0.14 | ***6.73*** | ***17.84*** | ***30.24*** | |
| HRG | V1 | 0.11 | 115.93 | 6.17 | 3.05 | 8.26 | 4.05 | 9.31 | 8.38 | 12.21 | 24.41 | 46.40 | 85 |
| | V2 | 0.08 | 113.79 | 5.89 | 2.91 | 4.83 | 3.72 | 9.77 | 8.81 | 13.66 | 27.75 | 49.23 | 40 |
| | V3 | 0.08 | 113.04 | 5.95 | 2.82 | 3.68 | 3.63 | 9.68 | 8.84 | 17.90 | 33.74 | 55.69 | 41 |
| | V4 | 0.07 | 109.34 | 6.23 | 2.71 | 3.03 | 3.64 | 9.42 | 8.92 | 15.61 | 30.68 | 53.07 | 50 |
| | V5 | 0.07 | 107.43 | 6.79 | 2.61 | 2.75 | 3.71 | 8.95 | 8.25 | 11.00 | 21.45 | 39.51 | 91 |
| | V5–V1 | -0.04 | -8.50 | 0.62 | -0.44 | -5.52 | -0.33 | -0.35 | -0.13 | ***-1.21*** | ***-2.95*** | ***-6.89*** | |

**Table 6**
**Year-by-year cumulative buy-and-hold returns on $V_f/P$ portfolios in the lowest arbitrage risk group (LRG)**

This table presents the cumulative buy-and-hold returns over one, two and three years (*RET*12, *RET*24 and *RET*36) on the lowest $V_f/P$-portfolio (V1) and on the highest $V_f/P$-portfolio (V5) in the lowest arbitrage risk group formed on each January from 1982 to 2002. As in Table 5, stocks are independently ranked on *SIZE*, *AGE*, *NANAL* and *PRC* in descending order and on *AQ*, *DISP*, *IVO* and *ILLIQ* in ascending order. Stocks in the highest quintile of arbitrage risk receive the score of one for each measure of arbitrage risk. The lowest arbitrage risk group consists of stocks that receive a zero score. Stocks are assigned to quintiles (V1 to V5) based on the value-to-price ratio ($V_f/P$) of the previous month. Portfolios are then held for 12, 24 and 36 months and portfolio returns are equally weighted. V5–V1 is the difference in value of the variable of interest between portfolio V5 and portfolio V1.

| | *RET*12 | | | *RET*24 | | | *RET*36 | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | V1 | V5 | V5–V1 | V1 | V5 | V5–V1 | V1 | V5 | V5–V1 |
| 1982 | 28.39 | 25.46 | -2.93 | 55.60 | 65.79 | 10.19 | 43.43 | 80.69 | 37.27 |
| 1983 | 29.25 | 26.23 | -3.01 | 21.90 | 42.40 | 20.50 | 46.64 | 93.42 | 46.78 |
| 1984 | -6.53 | 15.18 | 21.71 | 7.99 | 60.48 | 52.49 | 4.79 | 106.20 | 101.41 |
| 1985 | 21.80 | 39.78 | 17.98 | 36.45 | 79.38 | 42.93 | 54.34 | 84.38 | 30.04 |
| 1986 | 11.17 | 30.96 | 19.79 | 21.90 | 31.55 | 9.66 | 37.51 | 65.84 | 28.34 |
| 1987 | 5.32 | 1.90 | -3.42 | 23.76 | 31.97 | 8.21 | 49.86 | 74.87 | 25.01 |
| 1988 | 8.24 | 32.79 | 24.55 | 37.16 | 73.53 | 36.37 | 32.88 | 70.62 | 37.74 |
| 1989 | 21.65 | 32.94 | 11.29 | 7.25 | 24.50 | 17.25 | 35.88 | 67.75 | 31.87 |
| 1990 | -12.33 | -4.30 | 8.03 | 8.97 | 35.57 | 26.60 | 24.60 | 47.20 | 22.61 |
| 1991 | 27.59 | 40.98 | 13.39 | 46.14 | 58.66 | 12.52 | 57.96 | 86.13 | 28.17 |
| 1992 | 15.67 | 7.03 | -8.64 | 32.74 | 21.73 | -11.01 | 34.17 | 30.20 | -3.97 |
| 1993 | 23.28 | 6.05 | -17.23 | 25.32 | 16.48 | -8.84 | 42.33 | 51.33 | 9.00 |
| 1994 | -0.50 | 7.52 | 8.02 | 18.64 | 41.92 | 23.27 | 37.92 | 68.29 | 30.37 |
| 1995 | 30.28 | 32.96 | 2.68 | 54.14 | 54.35 | 0.21 | 91.79 | 108.57 | 16.78 |
| 1996 | 15.62 | 18.44 | 2.82 | 51.18 | 56.70 | 5.51 | 46.39 | 74.30 | 27.91 |
| 1997 | 20.16 | 33.25 | 13.09 | 9.59 | 43.94 | 34.35 | 38.06 | 44.69 | 6.63 |
| 1998 | 8.61 | -1.09 | -9.70 | 18.23 | 8.19 | -10.04 | 21.41 | 62.40 | 40.99 |
| 1999 | 37.90 | -8.47 | -46.37 | 43.63 | 13.64 | -29.99 | 41.10 | 31.72 | -9.38 |
| 2000 | -0.46 | 30.28 | 30.74 | -15.15 | 54.31 | 69.45 | -36.82 | 44.07 | 80.89 |
| 2001 | -15.91 | 21.88 | 37.79 | -26.91 | 9.74 | 36.65 | -1.34 | 57.16 | 58.50 |
| 2002 | -17.14 | -16.46 | 0.68 | 15.90 | 9.65 | -6.25 | 25.80 | 33.65 | 7.85 |
| Ave. | 12.00 | 17.78 | 5.77 | 23.54 | 39.74 | 16.19 | 34.70 | 65.88 | 31.18 |

**Table 7**
**Correlation matrix among different measures of arbitrage risk**

This table presents the time-series averages of monthly cross-sectional correlations among different measures of arbitrage risk. *SIZE* is the market value of equity. *AGE* is firm age. *AQ* is earnings quality. *NANAL* is the number of analysts following a stock. *DISP* is the dispersion in analysts' earnings forecasts. *IVO* is the idiosyncratic stock volatility. *PRC* is the stock price. The detailed definitions of these variables are given in Tables 2-4. The Spearman correlations are calculated each month from January 1982 to January 2002, and the means of the monthly correlations are reported. Stocks with prices of less than 5 dollars are excluded from our sample. For all the variables, values greater than the 0.995 fractile or less than the 0.005 fractile are set to equal the 0.995 and 0.005 fractile values, respectively. Significance levels are assessed using the mean and standard error of the monthly correlations. All the correlations are significantly different from both zero and one at the 1% level.

| Variable | *SIZE* | *AGE* | *AQ* | *NANAL* | *DISP* | *IVO* |
|---|---|---|---|---|---|---|
| *AGE* | 0.375 | | | | | |
| *AQ* | -0.146 | -0.252 | | | | |
| *NANAL* | 0.650 | 0.387 | -0.220 | | | |
| *DISP* | -0.078 | -0.037 | 0.088 | -0.067 | | |
| *IVO* | -0.289 | -0.429 | 0.452 | -0.345 | 0.227 | |
| *PRC* | 0.510 | 0.343 | -0.203 | 0.493 | -0.167 | -0.474 |

**Table 8**
**Fama-Macbeth regressions of individual stocks' 36-month buy-and-hold returns on different measures of arbitrage risk**

This table reports the regression tests of the incremental role of arbitrage risk in explaining the $V_f/P$ effect. The dependent variable is *RET*36 (in %). *SIZE* is the market value of equity. *BTMV* is the book-to-market ratio. $RET_{-6:-1}$ is the cumulative return over the past 6 months. $V_f/P$ is the value-to-price ratio. *AGE* is firm age. *AQ* is earnings quality. *NANAL* is the number of analysts following a stock. *DISP* is the dispersion in analysts' earnings forecasts. *IVO* is the idiosyncratic return volatility. *PRC* is the stock price. The detailed definitions of these variables are given in Tables 1-4. Fama and Macbeth (1973) cross-sectional regressions are estimated each month from January 1982 to January 2002, and the means of the monthly estimates are reported. Stocks with prices of less than 5 dollars are excluded. For all variables, values greater than the 0.995 fractile or less than the 0.005 fractile are set to the 0.995 and 0.005 fractile values, respectively. To normalize variables with large skewness, *SIZE*, *AGE*, *DISP* and *PRC* are logarithm values. The *t*-statistics are in parentheses and are computed as the mean divided by the standard error of the monthly estimates. The Newey and West (1987) procedure is used to adjust for serial correlations.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| *BETA* | 0.085 | 0.085 | 0.075 | 0.084 | 0.090 | 0.121 | 0.092 | 0.115 | 0.086 |
| | (2.65) | (2.72) | (2.65) | (2.64) | (2.83) | (4.57) | (2.91) | (4.33) | (3.47) |
| *Ln(SIZE)* | 0.013 | 0.010 | 0.007 | 0.000 | 0.012 | -0.009 | -0.006 | -0.033 | -0.022 |
| | (1.46) | (1.21) | (0.83) | (-0.01) | (1.31) | (-1.03) | (-0.96) | (-4.21) | (-2.44) |
| *BTMV* | 0.124 | 0.118 | 0.047 | 0.119 | 0.129 | 0.103 | 0.130 | 0.101 | 0.052 |
| | (5.25) | (5.13) | (2.59) | (4.95) | (5.09) | (5.02) | (5.37) | (4.75) | (2.89) |
| $RET_{-6:-1}$ | 0.119 | 0.121 | 0.159 | 0.124 | 0.119 | 0.113 | 0.076 | 0.121 | 0.155 |
| | (3.29) | (3.37) | (3.92) | (3.56) | (3.35) | (3.70) | (2.46) | (3.72) | (4.06) |
| $V_f/P$ | 0.060 | -0.112 | 0.142 | 0.047 | 0.071 | 0.106 | 0.013 | 0.010 | 0.104 |
| | (3.98) | (-2.09) | (11.02) | (2.83) | (4.54) | (6.28) | (0.43) | (0.10) | (1.13) |
| *Ln(AGE)* | | -0.013 | | | | | | -0.012 | -0.043 |
| | | (-1.14) | | | | | | (-1.31) | (-2.96) |
| $\boldsymbol{V_f/P \times Ln(AGE)}$ | | ***0.036*** | | | | | | ***0.018*** | ***0.010*** |
| | | ***(4.00)*** | | | | | | ***(2.10)*** | ***(0.80)*** |
| *AQ* (%) | | | -0.269 | | | | | | 0.092 |
| | | | (-0.68) | | | | | | (0.24) |
| $\boldsymbol{V_f/P \times AQ}$ **(%)** | | | ***-1.157*** | | | | | | ***-0.882*** |
| | | | ***(-4.00)*** | | | | | | ***(-2.39)*** |
| *NANAL* | | | | 0.002 | | | | 0.005 | 0.005 |
| | | | | (1.65) | | | | (3.23) | (2.07) |
| $\boldsymbol{V_f/P \times NANAL}$ | | | | ***0.001*** | | | | ***0.000*** | ***0.001*** |
| | | | | ***(2.13)*** | | | | ***(0.34)*** | ***(1.18)*** |
| *Ln*(1+*DISP*) | | | | | -0.034 | | | 0.005 | -0.030 |
| | | | | | (-1.17) | | | (0.22) | (-1.01) |
| $\boldsymbol{V_f/P \times Ln(1+DISP)}$ | | | | | ***-0.134*** | | | ***-0.108*** | ***-0.116*** |
| | | | | | ***(-4.75)*** | | | ***(-3.84)*** | ***(-3.08)*** |
| *IVO* (%) | | | | | | -0.075 | | -0.065 | 0.047 |
| | | | | | | (-3.73) | | (-3.36) | (-2.47) |
| $\boldsymbol{V_f/P \times IVO}$ **(%)** | | | | | | ***-0.017*** | | ***-0.012*** | ***-0.006*** |
| | | | | | | ***(-2.62)*** | | ***(-0.86)*** | ***(-0.37)*** |
| *Ln*(*PRC*) | | | | | | | 0.056 | 0.026 | 0.035 |
| | | | | | | | (2.38) | (1.01) | (1.52) |
| $\boldsymbol{V_f/P \times Ln(PRC)}$ | | | | | | | ***0.017*** | ***-0.003*** | ***-0.011*** |
| | | | | | | | ***(2.12)*** | ***(-0.17)*** | ***(-0.57)*** |
| Ave. N of stocks | 1794 | 1794 | 1034 | 1794 | 1636 | 1794 | 1794 | 1635 | 948 |
| Ave. Adj. $R^2$ | 0.077 | 0.079 | 0.079 | 0.080 | 0.084 | 0.092 | 0.084 | 0.102 | 0.104 |

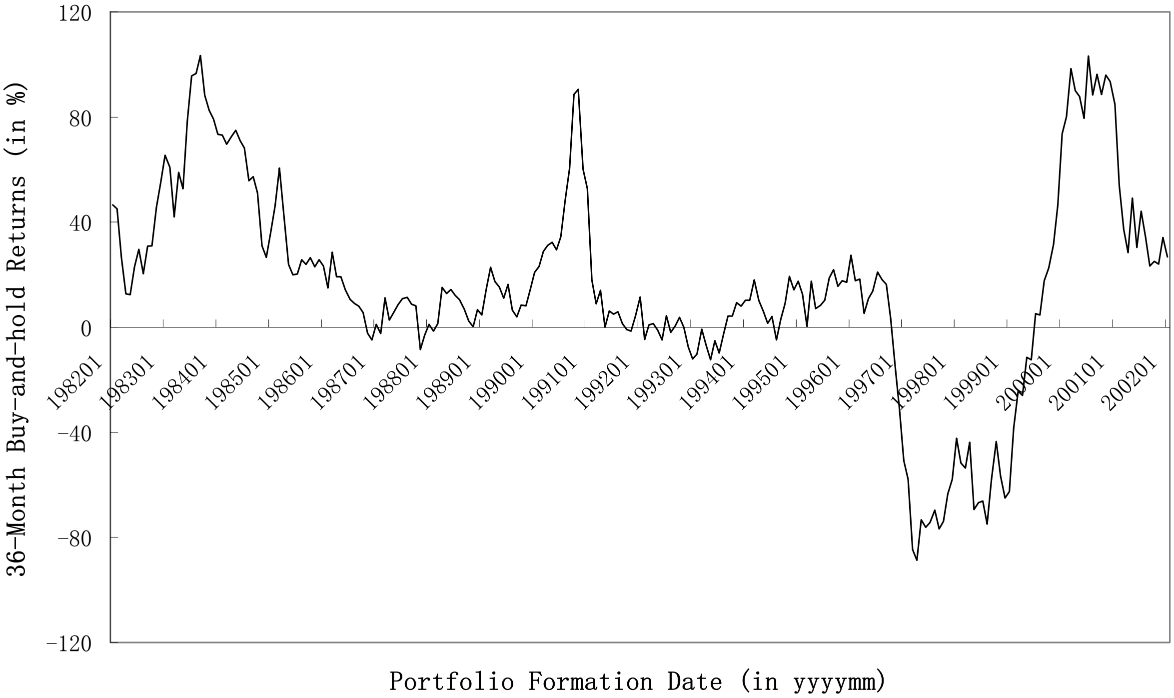


**Figure 1. The 36-month buy-and-hold returns (*RET*36) to a hedging strategy of buying the highest $V_f/P$ stocks and selling the lowest $V_f/P$ stocks.** Each month from January 1982 to January 2002, stocks are assigned to quintiles based on the value-to-price ratio ($V_f/P$) of the previous month. Five $V_f/P$-portfolios are formed and held for 36 months and portfolio returns are equally weighted. The figure plots the buy-and-hold return differentials between the highest $V_f/P$-portfolio and the lowest $V_f/P$-portfolio formed each month.

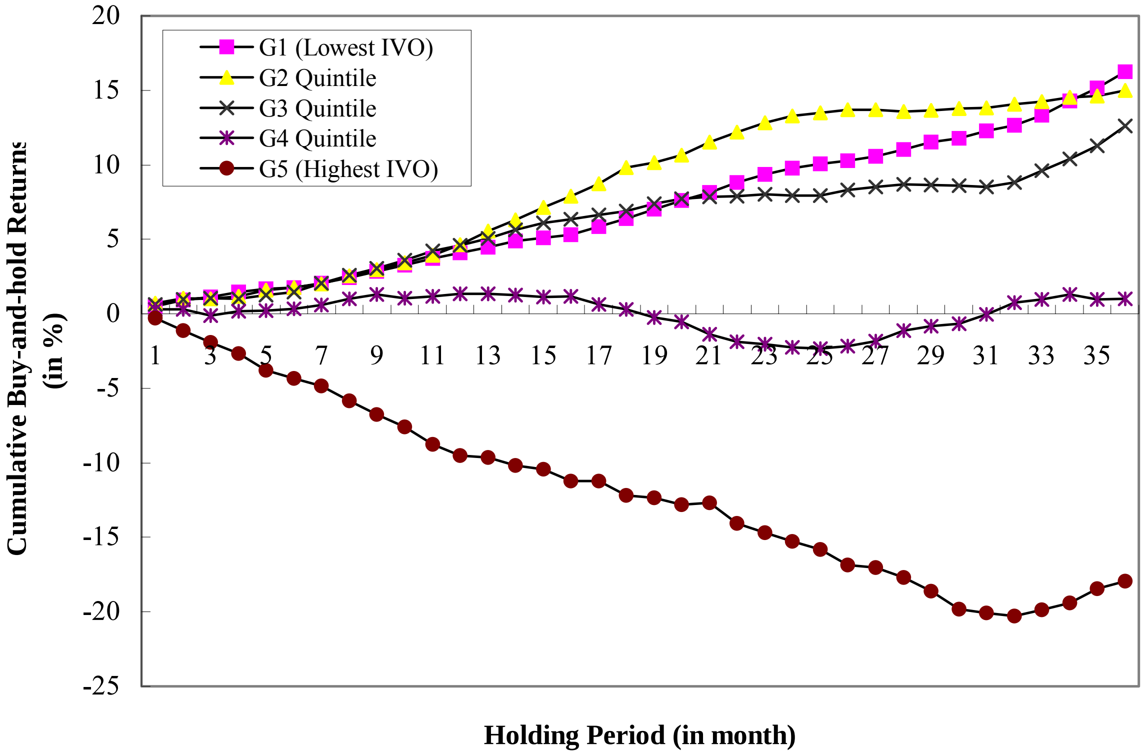


**Figure 2. Subperiod analysis.** Cumulative buy-and-hold returns to a hedging strategy of buying the highest $V_f/P$ stocks and selling the lowest $V_f/P$ stocks within different *IVO*-quintiles. Each month from July 1994 to January 2002, stocks are assigned to quintiles based on the value-to-price ratio ($V_f/P$) in the previous month. Stocks are also independently assigned to quintiles based on the idiosyncratic stock volatility (*IVO*) estimated using one-year daily returns ending at the previous month. The intersection of $V_f/P$-quintiles and *IVO*-quintiles results in 25 $V_f/P$-*IVO* portfolios. Portfolios are held for 36 months and portfolio returns are equally weighted. The figure plots the mean cumulative buy-and-hold return differentials between the highest $V_f/P$-portfolio and the lowest $V_f/P$-portfolio within each *IVO*-quintile.

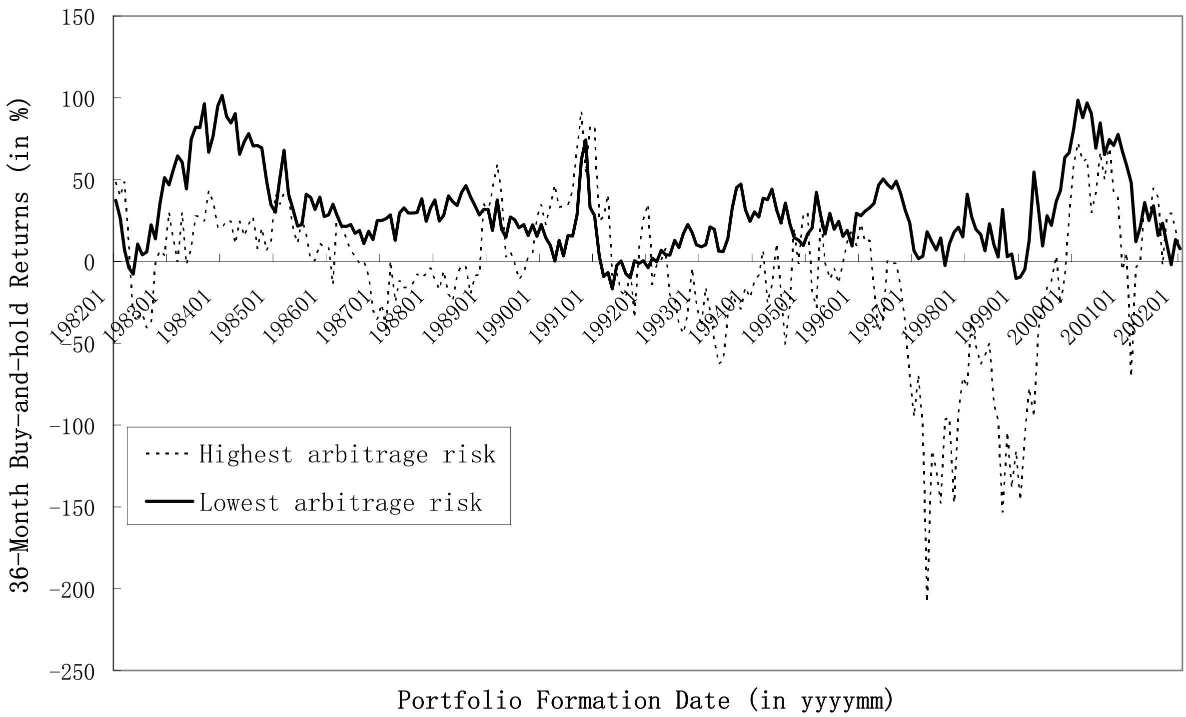


**Figure 3. The 36-month buy-and-hold returns (*RET*36) to a hedging strategy of buying the highest $V_f/P$ stocks and selling the lowest $V_f/P$ stocks in stocks with the highest arbitrage risk versus in stocks with the lowest arbitrage risk.** As in Table 5, each month from January 1982 to January 2002 stocks are independently ranked on the basis of *SIZE*, *AGE*, *NANAL* and *PRC* in descending order and on *AQ*, *DISP*, *IVO* and *ILLIQ* in ascending order. Stocks in the highest quintile of arbitrage risk receive the score of one for each measure of arbitrage risk. The highest arbitrage risk stocks are those that receive the score of four or more and the lowest arbitrage risk stocks are those that receive a zero score. Stocks are also assigned to quintiles based on the value-to-price ratio ($V_f/P$) in the previous month. Portfolios are held for 36 months and portfolio returns are equally weighted. The figure plots the buy-and-hold return differentials between the highest $V_f/P$-portfolio and the lowest $V_f/P$-portfolio formed each month within the highest arbitrage risk stocks and the lowest arbitrage risk stocks.