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The Limits to Arbitrage Revisited: The Accrual and Asset Growth Anomalies

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Using idiosyncratic volatility as a proxy for arbitrage costs, the authors found that the highly publicized accrual and asset growth anomalies exist because of high barriers to arbitrage, occurring predominantly in the universe of stocks with higher arbitrage risks. Therefore, investors who seek to profit from the accrual and asset growth anomalies must bear greater uncertainty in outcomes than was previously understood.

That such straightforward, well-publicized asset pricing anomalies as the accrual (Sloan 1996) and asset growth (Cooper, Gulen, and Schill 2008) effects are seemingly overlooked by investors and that these anomalies could persist for years despite the abundance of research describing them is puzzling. In our study, we sought to understand the extent to which the anomalous returns associated with these two effects can be attributed to higher arbitrage risks that arise from the lack of close substitutes. We focused on the accrual and asset growth effects because both have been shown to affect future returns negatively and are used extensively by active managers, yet the persistence of the return link is not well understood despite their widespread adoption in practice. Following prior research, we used idiosyncratic volatility (IVOL) from the Fama–French (1992) model to measure arbitrage risk. By doing so, we aimed to determine whether the anomalous accrual and asset growth effects are largely present among those stocks with higher IVOL, a group with meaningfully higher costs to arbitrage. If so, then such increased difficulty in arbitraging away their profitability may explain their persistence, even after becoming widely known.

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The importance of our investigation is bolstered by recent research that demonstrates the adverse impact of IVOL on effective arbitrage (e.g., Pontiff 2006). Exploring the influence of IVOL on extracting anomalous returns sheds light on investors' ability to profit from any associated mispricing. In particular, our model tests whether the accrual and asset growth anomalies exist in association with high IVOL. That is, do the accrual and asset growth anomalies exist among stocks with higher or lower levels of IVOL? If the predictive power of either or both of these anomalies is stronger among stocks with high IVOL, then doubt would be cast on whether at least some of their usefulness in predicting returns is attributable to the significant impact of arbitrage costs (as measured by IVOL).

Limits to Arbitrage

Our study expands the extensive body of research that explores limits to arbitrage (e.g., Pontiff 1996, 2006; Shleifer and Vishny 1997). Pontiff (2006) separated arbitrage costs into two types: transaction costs and holding costs. These two costs clearly hinder the ability of arbitrageurs to reduce mispricing through corrective trading. Transaction costs are incurred when positions are opened or closed and are proportional to initiating or terminating arbitrage positions, including bid–ask spreads, market impact, commissions, and dollar volume. As reported here and in the prior literature, the accrual and asset growth anomalies can be found in infrequently (annually) rebalanced portfolios and their return predictive power can last as long as three years (Sloan 1996; Cooper et al. 2008). Thus, transaction costs are unlikely to create significant limits to arbitrage, even if they are strongly related to the predictive power of these two anomalies.

Proportional to the amount of time the arbitrage position is held, holding costs include interest on margin requirements, short-sale costs (e.g., a haircut on a short-sale rebate rate), and the risk of holding a position with high IVOL. When confronted with holding a position with high IVOL, investors are less willing to engage in arbitrage because such a position is costly to hedge. This situation occurs when the position has no close substitutes that can be used for hedging. If the arbitrageur cannot perfectly hedge the undesired risk of the arbitrage position, then arbitrage involves unwanted risk. Therefore, among the various holding costs, idiosyncratic volatility is of particular importance to arbitrageurs and thus serves as our focus in measuring the relevant arbitrage costs.

To further understand how IVOL relates directly to arbitrage costs, consider the practice of arbitraging asset mispricing. In an ideal, riskless arbitrage, the arbitrageur uses a zero-cost arbitrage portfolio, with long and short positions, that fully hedges market risk and idiosyncratic risk, leaving only the desired mispricing effect. In other words, the arbitrageur seeks stocks that are highly negatively correlated along the mispriced dimensions and highly positively correlated (perfect substitutes) along other, undesired dimensions. The absence of such perfect substitutes in real markets makes arbitraging the desired mispricing effect imperfect and rather risky. Thus, in practice, the impact of IVOL makes the complete hedging away of undesired risk impossible. The higher the IVOL, the more difficult (and costly) the arbitrage effort.

Idiosyncratic volatility poses an important risk even for those who seek to exploit anomalies through infrequent portfolio rebalancing and relatively low transaction costs. In reality, high IVOL means that arbitrageurs remain exposed to the risk that any targeted mispricing may jump adversely in the short term, forcing them to liquidate their positions prematurely because of high leverage or capital constraints.

Although intuitively IVOL might seem to be relevant only to the undiversified arbitrageur, in fact, the diversification of the arbitrageur is irrelevant with respect to the arbitrageur's willingness to invest in a mispriced asset. That is, all risk-averse investors allocate a smaller portion of their portfolio to high-IVOL assets given a certain level of expected return, irrespective of the number of securities in the portfolio or the portfolio's level of diversification. This result can be seen in Treynor and Black (1973) and Pontiff (2006), who studied the investment allocation of arbitrageurs in a mean–variance portfolio optimization framework.[1]

In seeking to explain the persistence of the returns associated with the accrual and asset growth anomalies, we also sought to determine whether these anomalies arise from investor mispricing or from systematic market risk. This distinction is of paramount importance to investors. If the anomalies are related to systematic risk, then, in the spirit of the capital asset pricing model and the efficient market hypothesis, the excess returns can be viewed as fair compensation to investors for bearing that risk. But if the mispricing is driven by an imperfection (e.g., investor irrationality) connected with the anomaly, then the excess returns are likely to be ephemeral as investors come to understand their cognitive error and arbitrage away any excess returns.[2]

Investors' willingness to try to arbitrage anomalous returns is contingent on the expectation that excess returns will represent fair compensation for bearing related arbitrage risks. Given that investors allocate a smaller portion of their portfolio to high-IVOL assets than to low-IVOL assets, the excess returns associated with a particular anomaly may very well persist over time because the excess returns likely come with greater risk and uncertainty in outcomes. To the extent that anomalous returns are concentrated in high-IVOL stocks, an arbitrageur can expect to earn abnormal returns only by bearing higher undiversified risks. A strong, positive relationship between the return predictive power of the two anomalies and IVOL suggests an explanation of their return predictive power that is consistent with market mispricing and market efficiency as constrained by the limits to arbitrage. In short, a stronger anomaly mispricing signal associated with higher IVOL means that arbitrageurs face higher investment risk and, thus, higher arbitrage costs.

Accruals and Asset Growth

Recent research has examined the viability of such simple, fundamental anomalies as accruals and asset growth.[3] For the asset growth effect, research findings generally suggest that periods of significant asset expansion or capital expenditures tend to be followed by periods of negative abnormal stock returns. A central debate is about whether the asset growth effect can be attributed to mispricing or to systematic risk. On the one hand, advocates of the mispricing explanation argue that investors overreact to past information about positive asset growth by extrapolating the past growth rate into future periods.[4] Stock returns attenuate when investors are disappointed by the mean reversion of asset growth rates (see, e.g., Lakonishok, Shleifer, and Vishny 1994).

On the other hand, others argue that the asset growth effect is consistent with systematic risk. A growing literature points to the risk associated with the mix of a company's choosing to invest for future growth and existing company assets. The process of exercising growth options through capital investment presents the company with a dynamic asset structure that may contain different risks related to growth options and existing assets. These changes may induce time-varying risks that explain the asset growth effect (see, e.g., Berk, Green, and Naik 1999; Carlson, Fisher, and Giammarino 2004; Zhang 2005; Li, Livdan, and Zhang 2009).

In a seminal article on accruals, Sloan (1996) found a negative relationship between accruals and subsequent stock returns. In describing the return link, Sloan proposed a mispricing explanation whereby investors unduly fixate on earnings in valuing companies. Investors overestimate the overall persistence of earnings, however, because accruals reverse in subsequent periods and are much less persistent than cash flows. As investors recognize their initial estimation error, companies with high (low) levels of accruals generate low (high) stock returns.[5] Supported by the corporate finance surveys conducted by Graham, Harvey, and Rajgopal (2006), the mispricing explanation suggests that company managers seek to manage earnings in the short term through a variety of approaches, including accruals. As with asset growth, one may argue that the accrual effect is also attributable to systematic risk.

In our analysis, we sought to show whether these two anomalous effects are driven by systematic risk or market mispricing. To do so, we drew on an extensive body of research that explores the importance to investors of limits to arbitrage (e.g., Pontiff 1996, 2006; Shleifer and Vishny 1997; Mashruwala, Rajgopal, and Shevlin 2006). This literature seeks to understand the impact of arbitrage risk that arises from a lack of close substitutes. In our study, we used IVOL as a proxy for arbitrage risk and examined whether greater IVOL reduces investors' ability to eliminate the mispricing associated with market anomalies. A finding that anomalous effects are concentrated in high-IVOL stocks would lead us toward the mispricing explanation—that is, the anomaly exists because of the inability of investors to fully arbitrage away the gains.

We cannot precisely gauge the extent to which a specific mispricing signal can be arbitraged away. By examining the predictive power of the signal and the associated level of IVOL, however, we can infer the degree to which arbitrageurs are able to exploit the signal. Strong excess returns for a mispricing in conjunction with high levels of IVOL suggest that arbitrageurs have likely exploited the mispricing signal in a discernible way. Therefore, the mispricing is accompanied by a lack of close substitutes, which creates important risks for arbitrageurs.

Data and Sample

For 1962–2008, we obtained (1) financial statement data from Capital IQ Compustat's annual industrial and research files and (2) stock return data from CRSP's monthly stock return files. We restricted the sample to all nonfinancial companies with available data and assumed a four-month lag after the end of the fiscal year for which we gathered the Compustat data.[6] We formed the final sample by combining the companies in the Compustat and CRSP files that met all our criteria and had nonmissing observations for either the accrual or the asset growth measure. The final sample period for the combined accrual and asset growth sample was 1962–2008.

For exposition purposes, we followed prior research (e.g., Sloan 1996) and focused on those companies with a fiscal year-end in December. We obtained the accrual and asset growth measures that were available at the end of April and applied them to the subsequent 12-month (May–April) total returns (inclusive of dividends).

For delisted companies, the CRSP monthly return file excludes the returns from the delisting month unless the delisting date is at the end of the month. To create the effective delisting month returns for those excluded companies, we obtained the returns in the delisting month and the market cap on the delisting date from the CRSP daily return file and combined those returns with the delisting returns. For stocks whose delisting returns were unavailable from CRSP, we set the delisting return to –100 percent.

We measured IVOL as the standard deviation of the residual returns from the Fama–French (1993) three-factor model by regressing the daily returns of individual stocks in excess of the one-month T-bill rate ($R_{i,t} - R_{f,t}$) on the relevant factors. That is, for each stock i, we performed the following time-series regression:

$$R_{i,t} - R_{f,t} = a_i + b_i\left(R_{M,t} - R_{f,t}\right) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t},$$

where $R_{M,t} - R_{f,t}$, SMB, and HML represent the Fama–French market, size, and value factors, respectively. We used the daily stock and factor returns in the prior May–April period to estimate IVOL for each month t.

Model and Results

Using monthly Fama–MacBeth (1973) regressions, we regressed cross-sectional monthly stock returns over May–April on the accrual and asset growth measures calculated with the accounting data for the prior fiscal year. Fama–MacBeth regressions have the advantage of controlling for the effects of variates commonly shown to relate to stock returns, such as size and book-to-market. Accordingly, we estimated the following equation:

$$r_{t+1} = a_{0,t} + a_{1,t} Focus\ factor_t + a_{2,t} Size_t + a_{3,t} BM_t + \varepsilon_{i,t+1},$$

where

r_{t+1}	=	the monthly return
Focus factor	=	the accrual (*ACCRU*) or asset growth (*ASSETG*) measure
Size	=	the logarithm of the equity market capitalization at the end of April
BM	=	the logarithm of 1 plus the book-to-market ratio of equity

We measured the market value of equity at the end of each April. The book equity is the stockholders' book equity (Data216) plus balance sheet deferred taxes and investment tax credit (Data35) minus the book value of preferred stock (in the following order: Data56 or Data10 or Data130).

To avoid the danger of "factor fishing" in our reported results, we checked the robustness of our results across the various definitions proposed in the literature (see Appendix A for detailed definitions of all variables concerning accruals and asset growth). All our various measures yielded similar results. For ease of exposition, we present the results for the most straightforward definitions of the two anomaly variables in the main body of the article. We defined *ACCRU* as the annual change in net operating assets; we defined *ASSETG* as the annual change in total company assets. We report the results for the other accrual and asset growth measures in the three tables of Appendix B. We deflated all the accrual measures with the average total assets over years t and $t - 1$.

First, we estimated the model for the asset growth and accrual portfolios as in the prior literature and extended the study period through 2008. The results are reported in **Table 1**. The coefficient estimates are the time-series averages of coefficient estimates from monthly cross-sectional regressions, and the t-statistics are based on the distribution of the monthly coefficient estimates.

Consistent with the prior findings on accruals and asset growth, Table 1 shows that both *ASSETG* and *ACCRU* are inversely related to subsequent returns—and significantly so (at the 1 percent level). Our results are also robust with respect to the size and book-to-market effects. Consistent with Fama–French (1993), book-to-market is positively related to subsequent returns in both models and is significant at the 1 percent level. Size, however, exhibits little significance in either model. For the t-statistics, we applied the Newey–West procedure (1987) to correct for potential serial correlation.

Table 1. Cross-Sectional Regressions of Company Returns, 1962–2008
(t-statistics in parentheses)

Variable	Coefficient	Coefficient
A. Single- and three-variate regressions with asset growth		
ASSETG	–1.31***	–1.32***
	(–7.62)	(–7.42)
Size		0.01
		(0.70)
BM		0.67***
		(4.76)
Intercept	1.79***	1.77***
	(7.09)	(6.83)
B. Single- and three-variate regressions with accruals		
ACCRU	–1.35***	–1.38***
	(–10.74)	(–10.68)
Size		0.01
		(0.43)
BM		0.69***
		(4.78)
Intercept	1.83***	1.83***
	(7.27)	(7.00)

Notes: This table reports the results from Fama–MacBeth (1973) regressions based on the accrual and asset growth measures. Specifically, for each company i in year t, we first estimated factor loadings at the portfolio level and then assigned those loadings to each individual company i in the portfolio. This process provided the company-level information for estimating the following cross-sectional regression:

$$r_{t+1} = a_{0,t} + a_{1,t} Focus\ factor_t + a_{2,t} Size_t + a_{3,t} BM_t + \varepsilon_{i,t+1},$$

where r_{t+1} is the monthly return for the 12 months following the portfolio formation month, *Focus factor* represents the accrual (*ACCRU*) or asset growth (*ASSETG*) measure, *Size* is the logarithm of the equity market capitalization at the end of April, and *BM* is the logarithm of 1 plus the book-to-market ratio of equity. We measured the market value of equity at the end of April. The book equity is the stockholders' book equity plus balance sheet deferred taxes and investment tax credit minus the book value of preferred stock. The coefficient estimates are the time-series averages of coefficient estimates from the monthly cross-sectional regressions, and the t-statistics are based on the distribution of the monthly coefficient estimates. Column 2 reports the results for the single focus factor; in column 3, we also controlled for the Fama–French (1992) size and book-to-market effects.

***Significant at the 1 percent level.

Turning our attention to the main focus of our study, we considered the extent to which arbitrage risks impede investors' ability to arbitrage away the abnormal returns associated with *ACCRU* and *ASSETG* (see Table 1). For each month, we divided our sample into high- and low-IVOL companies, separated by the median IVOL. We then conducted separate Fama–MacBeth (1973) regressions for both IVOL groups. As discussed earlier, if the accrual and asset growth anomalies are costly to arbitrage, we would expect their return predictive power to be greater for the sample with high IVOL. In the extreme case, we might even observe that the two anomalies exist only among high-IVOL stocks.

Panel A of **Table 2** presents the results, which describe the strength of the relationship between the return predictive power of *ASSETG* and the level of IVOL. The results suggest that over the full period (1962–2008), the *ASSETG* effect in Table 1 is largely concentrated among the high-IVOL stocks.

In particular, we found that the estimated coefficient of *ASSETG* for the high-IVOL stocks in the three-variate regression is –2.68 and is highly significant. The corresponding estimated coefficient of *ASSETG* for the low-IVOL stocks, however, is only –0.03 and is insignificantly different from zero. Furthermore, the *t*-statistics for the high-IVOL group are strongly significant whether controlling for size and book-to-market or not. In comparison, the corresponding *t*-statistics for the low-IVOL group are insignificant. Overall, these results show that the negative relationship between *ASSETG* and abnormal returns in Table 1 exists predominantly among those stocks with relatively high IVOL. This finding suggests that investors who attempt to exploit abnormal returns for higher-asset-growth companies will incur much higher arbitrage costs and thus face highly uncertain outcomes. IVOL, therefore, plays an important role in increasing arbitrage costs for investors who seek to arbitrage the *ASSETG* effect. In fact, the entire existence of the asset growth anomaly may be the result of arbitrage risk arising from a lack of close substitutes.

We then analyzed the impact of IVOL on accruals. Panel B of Table 2 shows that the results for the accrual effect bear a striking similarity to those for the asset growth effect. For *ACCRU*, the *t*-statistics are highly significant in all models, whereas the high-IVOL stocks show a considerably higher magnitude for the estimated coefficients. This finding suggests that accrual profits are more significantly affected by the high-IVOL group than by the low-IVOL group. The results are

Table 2. Cross-Sectional Regressions for Low and High Idiosyncratic Volatility, 1962–2008
(*t*-statistics in parentheses)

Variable	Low	High	Low	High
A. Single- and three-variate regressions with asset growth				
ASSETG	0.01	–2.28***	–0.03	–2.68***
	(0.01)	(–9.83)	(–0.41)	(–11.43)
Size			–0.05***	0.39***
			(–8.26)	(3.31)
BM			0.02***	0.29***
			(2.93)	(8.08)
Intercept	0.37***	3.08***	0.27*	3.34***
	(2.44)	(7.89)	(1.83)	(8.77)
B. Single- and three-variate regressions with accruals				
ACCRU	–0.30***	–2.20***	–0.25***	–2.52***
	(–4.39)	(–11.90)	(–3.64)	(–13.75)
Size			–0.05***	0.35***
			(–8.10)	(2.93)
BM			0.02***	0.31***
			(3.01)	(8.28)
Intercept	0.52***	3.05***	0.37***	3.29***
	(3.33)	(7.97)	(2.36)	(8.76)

Notes: See notes to Table 1. This table reports the cross-sectional regressions for the universe of stocks divided into low-IVOL and high-IVOL companies, separated by the median IVOL.

*Significant at the 10 percent level.
***Significant at the 1 percent level.

the same when controlling for size and style. These findings suggest that the inverse relationship between *ACCRU* and abnormal returns (Table 1) exists predominantly among those stocks with relatively high IVOL. Moreover, using a variety of alternative measures for both asset growth and accruals, we obtained the same qualitative results (see Appendix B).

Because investment practitioners care about more than empirical results, on average, over long periods, we probed more deeply to explore how robust our findings are to the realities of practice. We did so by parsing the framework along a number of key dimensions. In particular, for each anomaly, we formed quintile portfolios, ranking each stock and placing it into one of five quintiles in accordance with its level of asset growth or accrual characteristic. Quintile 1 (5) corresponds to the quintile companies with the lowest (highest) characteristic. We then ran Fama–French (1993) three-factor regressions, which control for size and style, and a four-factor model with the additional momentum factor of Jegadeesh and Titman (1993). We report average monthly alphas sorted by the respective asset growth or accrual quintile. In addition, for each anomaly, we report the alphas for a zero-cost long–short spread, or arbitrage portfolio, which essentially measures the economic significance, or trading profitability, of the respective trading strategies. This portfolio is the difference between the lowest- and highest-ranked quintiles.

In addition to the full period, we also report quintile results for two subsample periods: 1962–1996 and 1997–2008. We chose the breakpoint 1996 because it roughly corresponds to the initial publication date of the seminal article on the accrual anomaly (Sloan 1996). Importantly, this breakpoint also allocates ample time to each subperiod, allowing for a proper scrutiny of results. Finally, all reported results are based on value-weighted portfolios, with characteristics and portfolios updated and rebalanced annually.[7] In untabulated results, we found that equal-weighted portfolios follow similar patterns.

These more comprehensive results confirm our earlier findings—namely, that the largest mispricing for the two anomalies is found among the highest-IVOL stocks, thereby limiting their effective arbitrage. For brevity and ease of exposition, we present the value-weighted, three-factor Fama–French (1993) adjusted portfolio results in graphic form. A comprehensive tabulation of our findings can be found in Appendix C.

Figure 1 depicts our further examination of the results in Table 1 as we parsed across various periods and quintiles, including a spread portfolio, all as previously described. As expected, the level of alpha is inversely related to both asset growth and accruals, as shown in Panel A and Panel B, respectively, of Figure 1. That is, the level of alpha for each anomaly progressively declines with each higher asset growth and accrual quintile.

Furthermore, as the difference portfolio (represented as "Low – High" in the figure) shows, both anomalies seemingly present traders with a powerful zero-cost spread portfolio alpha. As detailed in **Table C1** (Appendix C), all quintile spread portfolios are significant at the 1 percent level.[8] Finally, Figure 1 also demonstrates that the alphas for both anomalies are highly consistent for the two subperiods across every quintile, suggesting that the anomalous mispricings have not disappeared over time.

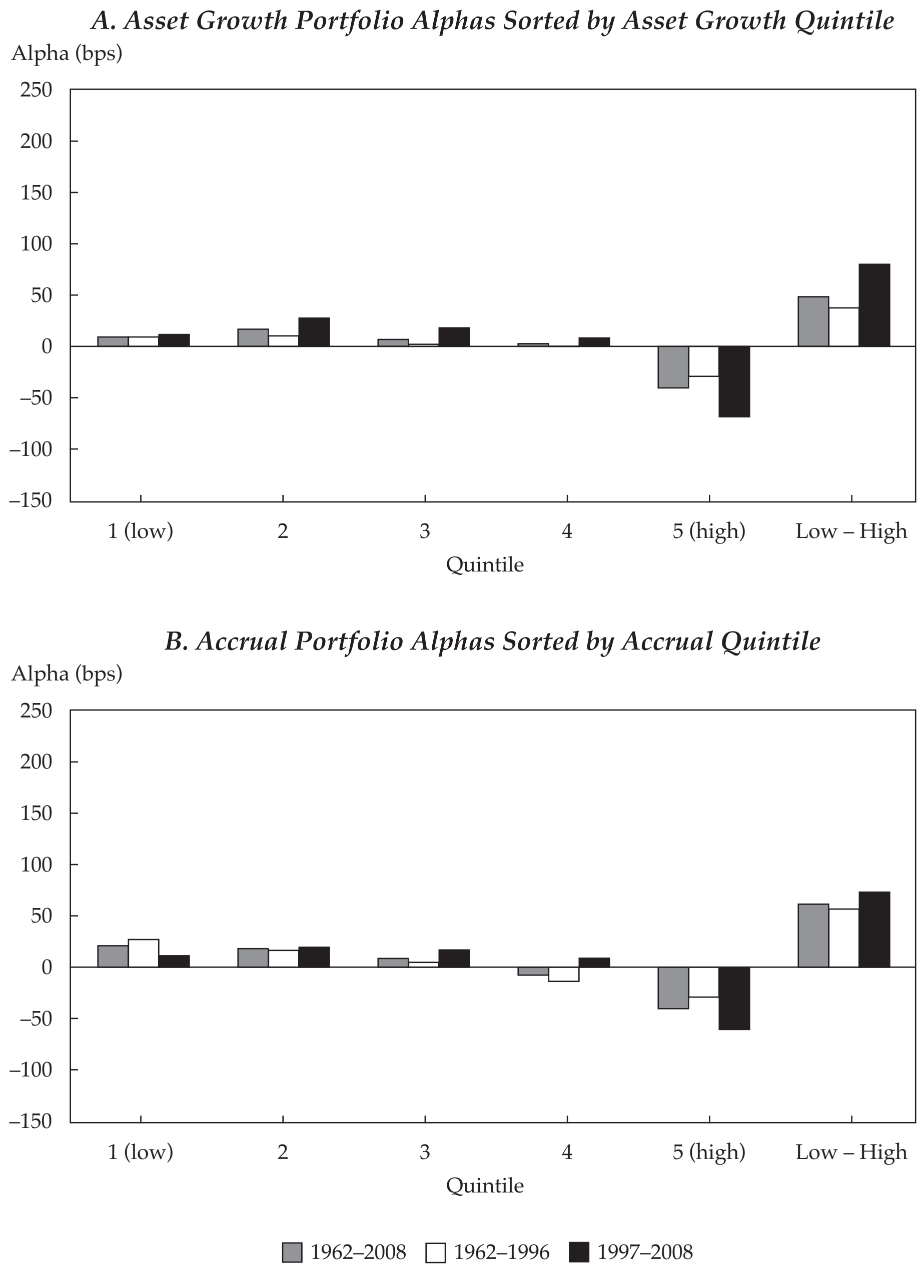
That the anomalous effects persist over time, even after becoming widely known, suggests either the existence of some pervasive risk factor (or factors) or that arbitrage costs have hindered investors' attempts to eliminate the effects. We next explored the latter scenario—the impact of higher costs via arbitrage. **Figure 2** presents a more detailed view of the results in Table 2. In Panel A, note that the alpha for asset growth is weak and exhibits no discernible pattern for the low-IVOL stocks across all asset growth quintiles. Moreover, as **Table C2** (Appendix C) shows, the spread portfolio alphas for all three low-IVOL periods are statistically insignificantly different from zero.

In Panel B of Figure 2, note that the asset growth anomaly alpha among the high-IVOL stocks for all asset growth quintiles contrasts markedly with the low-IVOL stocks in Panel A. Contrary to the paltry alphas found in the low-IVOL universe, the asset growth anomaly in the high-IVOL universe exhibits a highly discernible pattern, moving from a strongly positive alpha in Quintile 1 to a strongly negative alpha in Quintile 5. Importantly, for the high-IVOL stocks, the spread portfolio alphas for all three periods are large and highly statistically significant.[9]

The three-factor quintile alphas for the accrual anomaly are shown in **Figure 3** and Panel B of Table C2. Note that the quintile results for the accrual anomaly bear a strong resemblance to those for the asset growth anomaly in Figure 2 and Panel A of Table C2. Perhaps most importantly, for the accrual anomaly, arbitrageurs who attempt to extract the statistically significant spread portfolio alpha must do so among those stocks with higher levels of IVOL. The economic significance of the anomalous effect is, therefore, highly diminished.

Taken together, our research results indicate that the asset growth and accrual anomalies are both stronger among stocks with higher IVOL. In particular, both anomalies exist predominantly

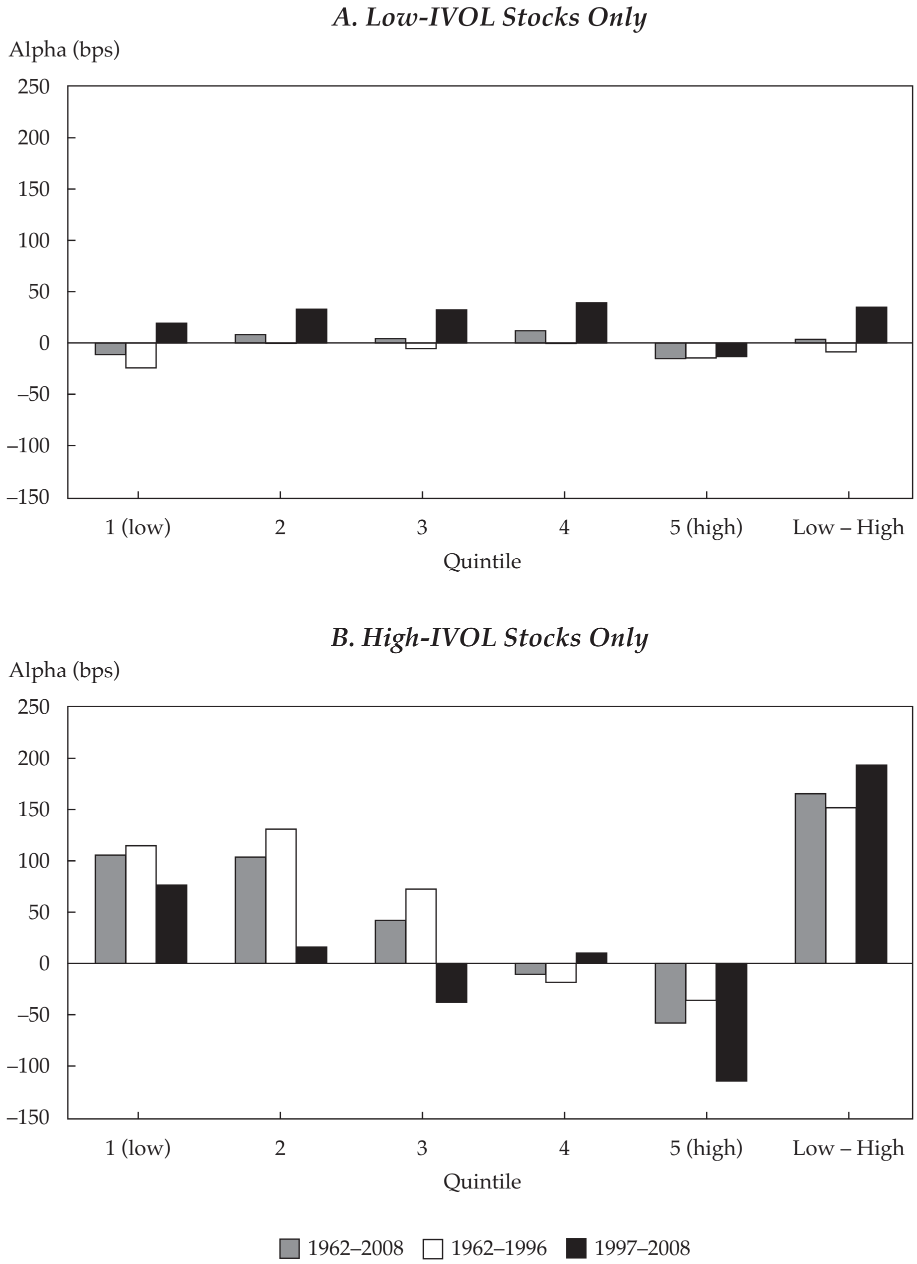
Figure 1. Three-Factor Portfolio Alphas Sorted by Quintile (Value-Weighted), 1962–2008



among the highest-IVOL stocks, thus obstructing their effective arbitrage. In the subset of low-IVOL stocks, the return predictive power of accruals and asset growth is much weaker. These results lead us to suggest that the observed profitability of these perceived anomalies likely results from high barriers to arbitrage as proxied by higher associated idiosyncratic risks. Our findings are robust to a battery of tests, including controlling for the well-known Fama–French (1993) size and book-to-market effects, and to alternative specifications of accruals and asset growth.

Our results for both the accrual and the asset growth effects support our thesis that investors who seek to profit from abnormal returns on long–short portfolios (formed as the difference between high and low quintiles) of accruals or asset growth face greater uncertainty than was previously understood.[10] Our findings suggest that the existence of these anomalous effects (Table 1) is largely attributable to the arbitrage risk arising from the lack of close substitutes, which hinders investors who seek to profit from the two anomalies.

Figure 2. Three-Factor Asset Growth Portfolio Alphas Sorted by Asset Growth Quintile (Value-Weighted), 1962–2008

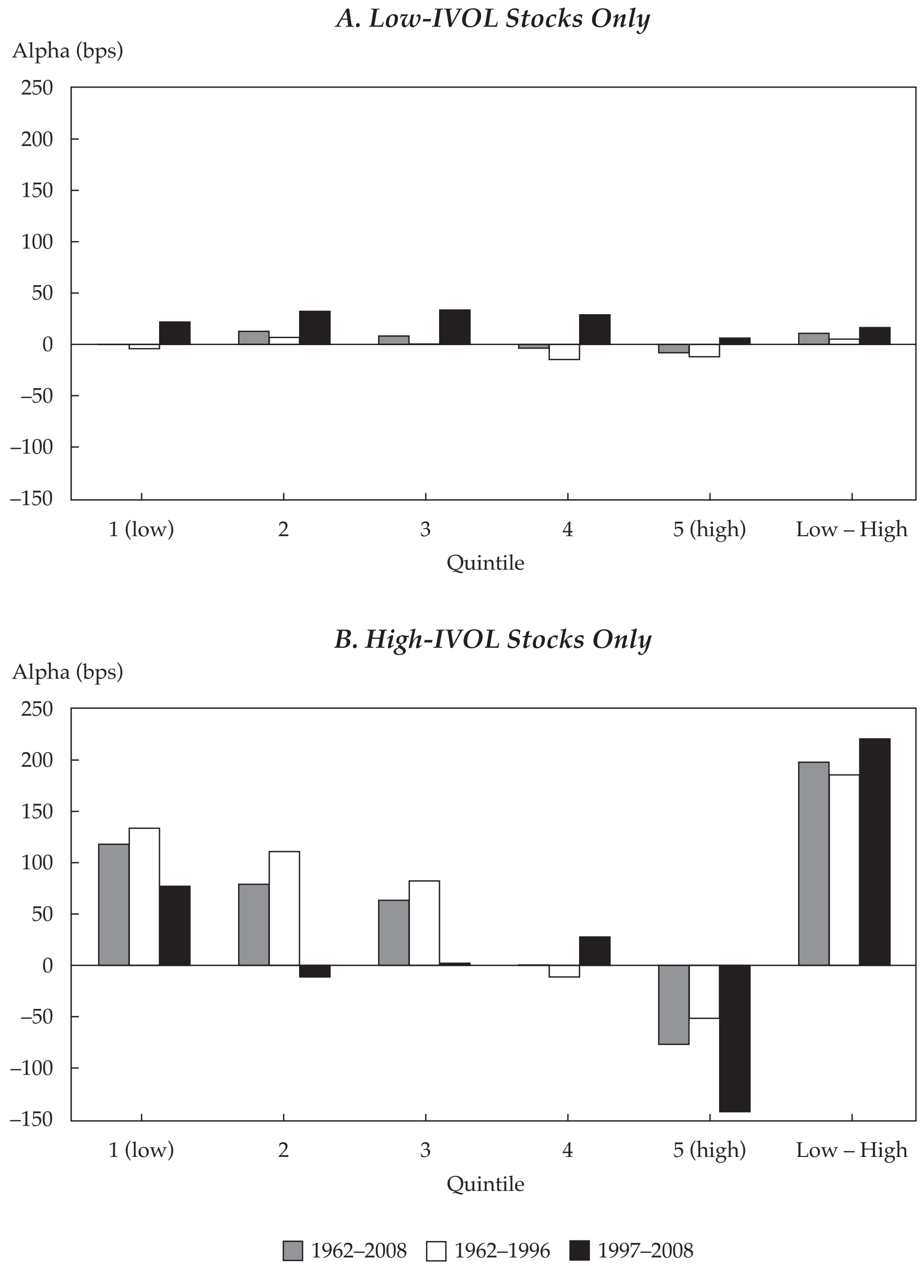


Conclusion

A central question for informed practitioners concerns the extent to which various alpha signals can be effectively used to generate trading profits. In a perfect world, no arbitrage risk arises from the lack of close substitutes because all arbitrage risk can be completely hedged away; thus, any investment signal with a link to excess returns can generate real trading profits. In reality, however, arbitrageurs are unable to fully hedge away all risks associated with a perfect arbitrage.

We focused on the risks associated with arbitraging two well-known anomalies: the accrual and asset growth effects. We found that the return link for both effects exists predominantly among stocks with high IVOL, which suggests that arbitrageurs face high arbitrage risk arising from a lack of close substitutes. Therefore, the accrual and asset growth effects are hard to arbitrage—that is, investors who seek to profit from these two market anomalies must bear a substantially higher risk with their trading positions. This risk meaningfully increases

Figure 3. Three-Factor Accrual Portfolio Alphas Sorted by Accrual Quintile (Value-Weighted), 1962–2008



the costs to arbitrage away the anomalous effects, which likely explains their persistence.

We contribute to the literature by showing that the arbitrage risk arising from the lack of close substitutes can create significant limits to arbitrage for investors who seek to reap profits from asset mispricing. Investors may, therefore, be unable to outperform the market on an after-cost basis even if seemingly significant mispricings are identified and persist over time. Most significantly, our findings highlight the importance of thoroughly investigating the arbitrage risk arising from the lack of close substitutes when exploring and implementing alpha signals. Our straightforward methodology could be a useful approach for practitioners who wish to verify the realistic opportunities to profit from an array of identified investment signals.

We are grateful for helpful comments from Luis Garcia-Feijóo.

This article qualifies for 1 CE credit.

Appendix A. Definitions of Variables

This appendix provides detailed definitions of all variables concerning accruals and asset growth. The data items referred to in this appendix are associated with the Compustat data definitions.

Asset Growth Variables

ASSETG: The annual change in total company assets. In our study, we focused on *CGS*, defined as (Compustat Data6, *t*)/(Data6, *t* – 1) – 1; from Cooper, Gulen, and Schill (2008), where (Data6) is the total assets of the company.

LSZ: [(Compustat Data3, *t*) – (Compustat Data3, *t* – 1) + (Data7, *t*) – (Data7, *t* – 1)]/(Data6, *t* – 1); from Lyandres, Sun, and Zhang (2008), where (Data3) is the inventories, (Data7) is the gross property, plant, and equipment, and (Data6) is the total assets of the company.

XING: (Compustat Data128, *t*)/(Data128, *t* – 1) – 1; from Xing (2008), where (Data128) is the capital expenditures of the company.

TWX: (Compustat Data128, *t*)/Average(Data128, *t* – 1, *t* – 2, *t* – 3) – 1; from Titman, Wei, and Xie (2004), where (Data128) is the capital expenditures of the company.

PS: (Compustat Data128, *t*)/(Data8, *t* – 1); from Polk and Sapienza (2009), where (Data128) is the capital expenditures and (Data 8) is the net property, plant, and equipment of the company.

AG: (Compustat Data128, *t*)/(Data128, *t* – 2) – 1; from Anderson and Garcia-Feijóo (2006), where (Data128) is the capital expenditures of the company.

Accrual Variables

ACCRU: The annual change in net operating assets.

Δ*NOA* is the change in net operating assets, which is defined as noncash assets less nondebt liabilities [(Total assets – Cash and short-term investments) – (Total liabilities – Total debt)]: [(Data6 – Data1) – (Data181 – Data9 – Data34)].

Total accruals (*TA*) via income statement: [Net income (from income statement) – Operating cash flow]/Average total assets.

TA via cash flow statement: Data123 – Data308 – Data311.

Current accruals is net income before extraordinary items – (Change in current assets – Change in current liability): EBITDA – [(ACT – ACT1) – (LCT – LCT1)].

DRS is a measure of total accruals as described in Table 1 from Dechow et al. (2008).

Appendix B. Accrual and Asset Growth Measures

In **Table B1**, **Table B2**, and **Table B3**, we report the results for various accrual and asset growth measures.

Table B1. The Return Predictive Power of Accruals and Asset Growth in Year $t + 1$, 1962–2008
(t-statistics in parentheses)

Variable	*TWX* 1	*TWX* 2	*XING* 3	*XING* 4	*AG* 5	*AG* 6	*PS* 7	*PS* 8	*LSZ* 9	*LSZ* 10	*CGS* 11	*CGS* 12
Asset growth	–0.88***	–0.89***	–0.81***	–0.84***	–0.82***	–0.81***	–0.91***	–0.92***	–1.29	–1.32***	–1.31***	–1.32***
	(–5.50)	(–5.56)	(–6.70)	(–6.75)	(–5.19)	(–5.15)	(–4.68)	(–4.72)	(–10.25)	(–10.12)	(–7.62)	(–7.42)
Size		0.01		0.01		0.01		0.01		0.01		0.01
		(0.64)		(0.54)		(0.52)		(0.75)		(0.63)	(6.63)	(0.70)
BM		2.61***		0.76***		2.64***		0.67***		0.66***		0.67***
		(3.62)		(4.84)		(3.58)		(4.86)		(4.64)		(4.76)
Intercept	1.57***	1.59***	1.55***	1.55***	1.54***	1.55***	1.59***	1.60***	1.80***	1.80***	1.79***	1.77***
	(5.89)	(5.85)	(6.15)	(5.96)	(6.07)	(5.99)	(7.52)	(7.44)	(6.83)	(6.62)	(7.09)	(6.83)
	TA (income statement)		*TA* (cash flow statement)		Δ*NOA*		Current Accruals		*DRS*			
Accruals	–0.51***	–0.50***	–0.50**	–0.50**	–1.35***	–1.38**	–0.45***	–0.47***	–1.26***	–1.26***		
	(–2.38)	(–2.34)	(–2.30)	(–2.29)	(–10.74)	(–10.68)	(–3.51)	(–3.57)	(–5.31)	(–5.25)		
Size		0.01***		0.01***		0.01		0.01		0.01***		
		(2.53)		(2.51)		(0.43)		(0.50)		(2.77)		
BM		3.39***		5.60***		0.69***		0.65***		3.37***		
		(–3.40)		(3.28)		(4.78)		(4.56)		(3.39)		
Intercept	1.20***	1.21***	1.19	1.22***	1.83***	1.83***	1.37***	1.35***	1.57***	1.58***		
	(2.64)	(2.60)	(2.61)	(2.62)	(7.27)	(7.00)	(5.53)	(5.22)	(3.63)	(3.56)		

Notes: See notes to Table 1. This table reports the results of Fama–MacBeth (1973) regressions based on various measures of accruals and asset growth. Column headings are the asset growth and accrual measures as defined in Appendix A.

**Significant at the 5 percent level.
***Significant at the 1 percent level.

Table B2. The Return Predictive Power of Asset Growth with Volatility, 1962–2008
(t-statistics in parentheses)

	TWX				*XING*				*AG*			
Variable	Low 1	High 2	Low 3	High 4	Low 5	High 6	Low 7	High 8	Low 9	High 10	Low 11	High 12
Asset growth	0.14	–1.49***	0.14	–1.79***	–0.08	–1.37***	–0.05	–1.60***	–0.04	–1.47***	–0.01	–1.76***
	(1.58)	(–7.56)	(1.58)	(–9.30)	(–1.45)	(–8.41)	(–0.94)	(–9.79)	(–0.40)	(–7.58)	(–0.14)	(–9.37)
Size			–0.04***	–0.25**			–0.05***	0.30***			–0.04***	0.24**
			(–7.58)	(–2.30)			(–7.98)	(2.55)			(–7.57)	(2.13)
BM			0.03**	0.33***			0.02***	0.35**			0.03**	0.33***
			(4.12)	(9.79)			(2.75)	(9.90)			(4.22)	(9.79)
Intercept	0.32*	2.73***	0.24	3.10***	0.42***	2.63***	0.28*	2.90***	0.41***	2.72***	0.32*	3.10***
	(1.92)	(6.87)	(1.44)	(8.01)	(2.58)	(7.01)	(1.73)	(7.91)	(2.46)	(6.98)	(1.92)	(8.18)
	PS				*LSZ*				*CGS*			
Asset growth	–0.47***	–1.82***	–0.44***	–2.42***	–0.07	–2.15***	–0.06	–2.50***	0.01	–2.28***	–0.03	–2.68***
	(–4.62)	(–8.64)	(–4.50)	(–11.83)	(–1.06)	(–11.80)	(–0.92)	(–13.56)	(0.01)	(–9.83)	(–0.41)	(–11.43)
Size			–0.05***	0.34***			–0.05***	0.38***			–0.05***	0.39***
			(–6.20)	(2.90)			(–8.21)	(3.19)			(–8.26)	(3.31)
BM			0.02**	0.42***			0.02***	0.30***			0.02***	0.29***
			(2.13)	(10.21)			(3.00)	(8.26)			(2.93)	(8.08)
Intercept	0.56***	2.83***	0.44***	3.32***	0.40***	3.02***	0.27*	3.29***	0.37***	3.08***	0.27*	3.34***
	(3.73)	(8.31)	(2.99)	(9.69)	(2.48)	(7.70)	(1.70)	(8.65)	(2.44)	(7.89)	(1.83)	(8.77)

Notes: See notes to Table B1. This table reports the results of various asset growth metrics for the universe of stocks divided into low-IVOL and high-IVOL companies, separated by the median IVOL.

*Significant at the 10 percent level.
**Significant at the 5 percent level.
***Significant at the 1 percent level.

Table B3. The Return Predictive Power of Accruals with Volatility, 1962–2008
(*t*-statistics in parentheses)

	TA (income statement)				*TA* (cash flow statement)				ΔNOA			
Variable	Low 1	High 2	Low 3	High 4	Low 5	High 6	Low 7	High 8	Low 9	High 10	Low 11	High 12
Accruals	–0.28***	–0.58***	–0.19**	–0.52**	–0.25***	–0.58**	–0.16*	–0.54**	–0.30***	–2.20***	–0.25***	–2.52***
	(–3.01)	(–2.13)	(–2.07)	(–2.00)	(–2.70)	(–2.12)	(–1.78)	(–2.05)	(–4.39)	(–11.90)	(–3.64)	(–13.75)
Size			–0.03***	0.85***			–0.03***	0.85***			–0.05***	0.35***
			(–6.83)	(6.49)			(–6.88)	(6.39)			(–8.10)	(2.93)
BM			–0.02**	–0.10***			–0.02**	–0.13**			–0.02**	–0.31**
			(–2.13)	(–5.17)			(–2.23)	(–5.30)			(–3.01)	(–8.28)
Intercept	0.57***	1.77***	0.34	1.39***	0.56***	1.77***	0.33	1.41***	0.52***	3.05***	0.37***	3.29***
	(2.41)	(2.69)	(1.48)	(2.36)	(2.34)	(2.68)	(1.42)	(2.40)	(3.33)	(7.97)	(2.36)	(8.76)
	Current Accruals				*DRS*							
Accruals	–0.41***	–0.72***	–0.36***	–0.67***	0.04	–2.01***	0.16	–2.14***				
	(–7.36)	(–4.08)	(–6.78)	(–3.83)	(0.36)	(–6.06)	(1.47)	(–6.67)				
Size			–0.05***	0.34***			–0.03***	0.92***				
			(–7.98)	(2.76)			(–6.87)	(7.12)				
BM			–0.02**	–0.29***			–0.02***	–0.10**				
			(–2.58)	(–8.10)			(–2.33)	(–5.20)				
Intercept	0.57***	2.31***	0.43***	2.36***	0.42*	2.48***	0.17	2.18***				
	(3.55)	(6.05)	(2.74)	(6.42)	(1.89)	(3.78)	(0.81)	(3.63)				

Notes: See notes to Table B1. This table reports the results of various accrual metrics for the universe of stocks divided into low-IVOL and high-IVOL companies, separated by the median IVOL.

*Significant at the 10 percent level.
**Significant at the 5 percent level.
***Significant at the 1 percent level.

Appendix C. Alphas for Three- and Four-Factor Quintile Portfolios

In Table C1 and Table C2, we report the results for three- and four-factor quintile portfolios sorted by level of accrual or asset growth characteristic.

Table C1. Monthly Factor-Adjusted Returns for Value-Weighted Quintile Portfolios (*t*-statistics in parentheses)

	Three-Factor Model Alphas (bps)			Four-Factor Model Alphas (bps)		
Rank	1962–2008	1962–1996	1997–2008	1962–2008	1962–1996	1997–2008
A. Asset growth						
1	9.31	10.19	12.25	25.36**	16.80*	35.01
	(0.84)	(1.04)	(0.41)	(1.96)	(1.70)	(1.06)
2	17.45***	11.76*	28.52	29.55***	17.69***	48.43***
	(2.42)	(1.89)	(1.48)	(3.96)	(2.81)	(2.74)
3	7.22	3.17	18.39	13.78***	8.68	26.68**
	(1.29)	(0.56)	(1.33)	(2.49)	(1.50)	(1.98)
4	1.34	–0.55	8.83	11.46	4.91	22.29
	(0.18)	(–0.08)	(0.45)	(1.47)	(0.67)	(1.15)
5	–40.20***	–28.59***	–69.36***	–22.05*	–18.28*	–46.19
	(–3.70)	(–2.99)	(–2.46)	(–1.83)	(–1.92)	(–1.55)
1 – 5	49.51***	38.78***	81.61*	47.41***	35.08***	81.20
	(3.19)	(2.75)	(1.96)	(2.46)	(2.46)	(1.61)
B. Accruals						
1	21.16**	26.48***	11.43	30.44***	22.33**	34.00
	(2.09)	(2.54)	(0.48)	(2.77)	(2.28)	(1.36)
2	18.33***	18.13***	19.07	24.25***	18.95***	32.45**
	(2.80)	(2.78)	(1.18)	(3.52)	(2.83)	(2.06)
3	8.83	4.92	17.75	17.15***	12.30**	26.97**
	(1.44)	(0.79)	(1.25)	(2.88)	(1.97)	(1.98)
4	–9.00	–15.95**	8.77	4.52	–5.59	24.85
	(–1.18)	(–2.15)	(0.47)	(0.59)	(–0.77)	(1.36)
5	–41.31***	–30.62***	–62.49***	–23.49***	–18.57**	–41.12*
	(–4.19)	(–3.36)	(–2.59)	(–2.34)	(–2.09)	(–1.65)
1 – 5	62.47***	57.09***	73.92***	53.93***	40.90***	75.12**
	(4.77)	(4.13)	(2.43)	(3.71)	(3.12)	(2.09)

Notes: This table reports the average monthly alphas for value-weighted quintile portfolios whereby each ranked stock is placed into one of five quintiles according to its level of asset growth or accrual characteristic. Quintile 1 (5) corresponds to the quintile companies with the lowest (highest) characteristic as calculated in the prior year. Columns 2–4 report the results for Fama–French (1993) three-factor regressions, which control for size and style; columns 5–7 report the results for a four-factor model that also controls for the momentum factor of Jegadeesh and Titman (1993). The table also reports the alphas for a zero-cost spread portfolio, calculated as the difference between the lowest- and highest-ranked quintiles.

*Significant at the 10 percent level.
**Significant at the 5 percent level.
***Significant at the 1 percent level.

Table C2. Monthly Factor-Adjusted Returns for Value-Weighted Quintile Portfolios Grouped by Level of IVOL
(*t*-statistics in parentheses)

	Three-Factor Model Alphas (bps)			Four-Factor Model Alphas (bps)		
Rank	1962–2008	1962–1996	1997–2008	1962–2008	1962–1996	1997–2008
A. Asset growth						
Low-IVOL stocks						
1	–12.41	–24.25**	21.67	–4.58	–13.88	27.48
	(–1.27)	(–2.16)	(1.15)	(–0.47)	(–1.23)	(1.45)
2	9.42	–1.17	34.04**	17.93***	7.22	44.97***
	(1.42)	(–0.17)	(2.29)	(2.83)	(1.13)	(3.13)
3	5.12	–4.89	32.47***	9.40	1.97	34.96***
	(0.88)	(–0.77)	(2.62)	(1.62)	(0.31)	(2.75)
4	12.68*	2.88	41.02***	16.78***	6.30	46.53***
	(1.84)	(0.43)	(2.39)	(2.35)	(0.88)	(2.68)
5	–15.87*	–15.73*	–13.75	–11.69	–12.78	–6.83
	(–1.80)	(–1.68)	(–0.69)	(–1.25)	(–1.28)	(–0.33)
1 – 5	3.46	–8.52	35.42	7.11	–1.10	34.31
	(0.26)	(–0.57)	(1.37)	(0.52)	(–0.07)	(1.25)
High-IVOL stocks						
1	104.84***	115.07***	76.89	145.48***	122.73***	143.61***
	(4.65)	(6.21)	(1.28)	(5.61)	(6.33)	(2.46)
2	102.44***	129.43***	16.52	139.07***	133.35***	86.18
	(4.31)	(6.51)	(0.26)	(4.92)	(6.48)	(1.38)
3	41.79**	71.40***	–37.83	77.95***	83.36***	20.44
	(1.97)	(3.73)	(–0.66)	(3.89)	(4.19)	(0.42)
4	–10.15	–17.94	11.75	21.45	–5.00	54.32
	(–0.50)	(–0.96)	(0.23)	(1.04)	(–0.26)	(1.15)
5	–58.09***	–35.88**	–113.35***	–22.59	–17.75	–70.73***
	(–3.08)	(–2.06)	(–2.57)	(–1.20)	(–1.05)	(–1.65)
1 – 5	162.93***	150.95***	190.24***	168.07***	140.48***	214.34***
	(6.88)	(6.79)	(3.06)	(6.52)	(6.31)	(3.31)
B. Accruals						
Low-IVOL stocks						
1	0.25	–6.79	21.95	3.50	–5.46	28.61*
	(0.03)	(–0.70)	(1.42)	(0.40)	(–0.53)	(1.84)
2	12.92**	5.95	31.74**	17.76***	10.63	39.57***
	(2.00)	(0.90)	(2.20)	(2.75)	(1.56)	(2.75)
3	8.42	–0.41	32.71***	12.92**	6.39	34.90***
	(1.36)	(–0.06)	(2.43)	(2.05)	(0.97)	(2.46)
4	–4.56	–16.90**	28.15*	1.44	–10.90	36.07***
	(–0.66)	(–2.19)	(1.93)	(0.20)	(–1.41)	(2.35)
5	–9.96	–13.91	5.08	–5.15	–8.82	12.04
	(–1.18)	(–1.53)	(0.29)	(–0.60)	(–0.96)	(0.68)
1 – 5	10.21	7.12	16.86	8.64	3.37	16.58
	(0.87)	(0.51)	(0.80)	(0.72)	(0.23)	(0.77)
High-IVOL stocks						
1	117.33***	131.40***	76.15	152.94***	131.45***	141.40***
	(5.66)	(7.06)	(1.46)	(6.90)	(6.83)	(3.04)
2	78.14***	109.37***	–12.06	99.67***	106.94***	32.66
	(3.75)	(5.77)	(–0.22)	(4.37)	(5.38)	(0.64)
3	62.92***	81.74***	2.03	91.28***	95.21***	42.88
	(3.14)	(4.08)	(0.04)	(4.48)	(4.78)	(0.95)

(continued)

Table C2. Monthly Factor-Adjusted Returns for Value-Weighted Quintile Portfolios Grouped by Level of IVOL
(*t*-statistics in parentheses) (continued)

	Three-Factor Model Alphas (bps)			Four-Factor Model Alphas (bps)		
Rank	1962–2008	1962–1996	1997–2008	1962–2008	1962–1996	1997–2008
4	–1.33	–12.69	28.34	35.51*	9.94	69.59
	(–0.06)	(–0.67)	(0.55)	(1.73)	(0.52)	(1.47)
5	–78.03***	–51.62***	–141.89***	–36.01*	–33.15*	–86.61*
	(–3.86)	(–2.80)	(–2.88)	(–1.73)	(–1.82)	(–1.84)
1 – 5	195.35***	183.03***	218.04***	188.95***	164.60***	228.02***
	(8.93)	(8.07)	(4.20)	(8.16)	(7.26)	(4.06)

Notes: See notes to Table C1. This table reports the Fama–French (1993) regression results for the universe of stocks divided into low-IVOL and high-IVOL companies, separated by the median IVOL.

*Significant at the 10 percent level.
**Significant at the 5 percent level.
***Significant at the 1 percent level.

Notes

1. Treynor and Black (1973) and Pontiff (2006) showed that the amount an arbitrageur allocates to a particular mispriced asset is a function of the asset's alpha and IVOL and the arbitrageur's risk aversion. Thus, the amount invested in the mispriced asset does not vary with the number of securities in the portfolio or the portfolio's diversification.
2. See Li and Sullivan (2010a, 2010b, 2011b) for an exploration of the systematic risk versus mispricing explanation for the low-risk anomaly and the implications of the asset growth anomaly internationally.
3. For asset growth, see, for example, Anderson and Garcia-Feijóo (2006); Cooper, Gulen, and Schill (2008); Lipson, Mortal, and Schill (2009); Li and Sullivan (2011b); Fama and French (2008); Lyandres, Sun, and Zhang (2008); Polk and Sapienza (2009); Titman, Wei, and Xie (2004); Xing (2008). For accruals, see, for example, Sloan (1996); Xie (2001); Hribar and Collins (2002); Fairfield, Whisenant, and Yohn (2003); Dechow, Richardson, and Sloan (2008).
4. For example, the asset growth effect is consistent with investor underappreciation of managerial empire building. As shown in surveys (see Graham, Harvey, and Rajgopal 2006), financial executives are willing to pursue value-destructive capital investment activities.
5. For example, consider the impact of inventory accruals when company managers overestimate sales and thus need to draw down excess inventory in future periods. Another, more sinister example involves the accounts payable shenanigan of "channel stuffing."
6. Alford, Jones, and Zmijewski (1994) reported that the financial statements of almost all companies are publicly available by then.
7. With the use of value-weighted portfolios and annual rebalancing, our findings are highly unlikely to be meaningfully altered by transaction costs.
8. From the estimated coefficient of the difference portfolio, adjusted for the three Fama–French (1993) factors for 1962–2008, we calculated the implied annualized abnormal monthly return as 6.11 percent [= $(1 + 0.4951 \text{ percent})^{12} - 1$] for asset growth and 7.76 percent for accruals.
9. Over the full sample period, the average annualized alpha is a factor-adjusted 21.40 percent.
10. See Li and Sullivan (2011a) for a thorough discussion of various unintended consequences of active models.

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