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

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Abstract

We find that the highly publicized accrual and asset growth anomalies exist due to high barriers to arbitrage. Using idiosyncratic volatility as a proxy for arbitrage costs, we find that both anomalies exist predominantly in the universe of stocks with higher arbitrage risks. Investors seeking to profit from the accrual and asset growth anomalies must therefore bear greater uncertainty in outcomes than previously understood.

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It is puzzling that such straightforward asset pricing anomalies like the well-publicized accruals (Sloan 1996) and asset growth (Cooper et al. 2008) effects are seemingly overlooked by investors and that these anomalies could persist for years despite the abundance of research describing them.[1] In this paper we seek to understand the extent to which the anomalous returns associated with these two effects can be attributed to higher arbitrage risks due to the lack of close substitutes. The accrual and asset growth effects are of particular interest in that they have both been shown to negatively relate to future returns and are used extensively by active managers, but the persistence of the return link is not yet well understood. Following prior research, we use idiosyncratic volatility (IVOL) from the Fama-French (1992) model to measure arbitrage risk. We find that the anomalous accruals and asset growth effects are largely present only among those stocks with higher IVOL, a group with meaningfully higher costs to arbitrage. Such increased difficulty in arbitraging away their profitability, may therefore explain their persistence, even after becoming widely known.

The importance of our investigation is bolstered by recent research which demonstrates the adverse impact IVOL imparts on effective arbitrage (e.g., Pontiff (2006)). Exploring the influence IVOL imposes on extracting anomalous returns sheds light on investors' ability to profit from any associated mispricing. In particular, our model tests whether the accruals and asset growth anomalies exist in association with high IVOL. That is, Do the accruals and asset growth anomalies exist among

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[1] We follow the prior literature and refer to these as the accruals effect (Sloan 1996) and asset growth effect (Cooper et al. (2008)).

stocks with higher or lower levels of IVOL? Should the predictive power of either or both of these two anomalies be stronger among stocks with high IVOL then this casts doubt on whether at least some their usefulness in predicting returns is attributable to the costly impact of arbitrage costs (as measured through IVOL).

Our research results indicate that the asset growth and accrual anomalies are both indeed stronger among stocks with higher IVOL. In particular, we find that both anomalies exist predominantly among the highest IVOL stocks, thus obstructing their effective arbitrage. In the subset of low IVOL stocks, we find that 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 are consistent with the notion that higher arbitrage risks result from a lack of close substitutes thus creating important limits for arbitrageurs seeking to exploit these two anomalies. In short, we find that arbitrageurs must bear higher risks in attempting to profit from mispricing associated with the accruals and asset growth effects. Accordingly, although our results suggest that these two anomalies are due to market pricing instead of systematic risk, the existence of these two anomalies may *not* provide strong evidence against market efficiency.

Limits to Arbitrage

Our research effort extends a deep extant body of research that explores limits to arbitrage (e.g., Pontiff (1996, 2006), Shleifer and Vishny (1997)). Pontiff (2006) separates 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 and terminating arbitrage positions including bid-ask spreads, market impact, commissions, and dollar volume. We suggest that for the accruals and asset growth anomalies, transactions costs are unlikely to create significant limits to arbitrage, even if they are significantly related to the return predictive power of these two anomalies. This is because, as reported here and in the prior literature, these two anomalies can be found in infrequently rebalanced portfolios (annually) and their predictive power can last for as long as three years (Sloan 1996 and Cooper, et al (2008)).

Holding costs represent the second type of arbitrage cost and are those costs proportional to the amount of time the arbitrage position is held. Holding costs include interest on margin requirements, short sale costs (e.g., the haircut on short sale rebate rate) and the risk associated with holding a position that possesses high IVOL. When confronted with holding a position with high IVOL, the investor is less willing to engage in arbitrage because the position is costly to hedge. This situation occurs when the position has a lack of close substitutes that can be used for specific hedging purposes. 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 as such serves as our point of focus in measuring the relevant arbitrage costs.

To further explain how IVOL directly relates to arbitrage costs, consider the practice of arbitraging asset mispricing. In an ideal riskless arbitrage, the arbitrageur employs a zero cost arbitrage portfolio through 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 while being highly positively correlated (perfect substitutes) in 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) is the arbitrage effort.

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

While it may seem intuitive that IVOL is only relevant for the undiversified arbitrageur, in fact the diversification of the arbitrageur is irrelevant with regards to the willingness of the arbitrageur 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), both of whom study the investment allocation of arbitrageurs in a mean-variance portfolio optimization framework.[2]

[2] The cited research shows that the amount an arbitrageur will dedicate to a particular mispriced asset is a function of the asset's alpha, it's IVOL, and his 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.

In seeking to better understand the persistence of anomalous returns associated with accruals and asset growth, our results also help to differentiate whether these anomalies derive from investor mispricing or from systematic market risk. This distinction is of essential importance to investors. Should the anomaly in question be related to systematic risk, then, in the spirit of CAPM and the efficient market hypothesis, the excess returns can be viewed as fair compensation to investors to taking that risk. If the mispricing is instead driven by an imperfection such as 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 return.

Investors' willingness to attempt arbitraging anomalous returns is contingent on the expectation that excess returns represent fair compensation for bearing related arbitrage risks. As mentioned, investors allocate a smaller portion of their portfolio to high IVOL assets. As such, the observed excess returns associated with a particular anomalous effect may very well persist over time because their excess returns likely come with greater risk and uncertainty in outcomes. To the extent anomalous returns are concentrated in high IVOL stocks, an arbitrageur can expect to earn abnormal returns only through bearing higher un-diversified risks. A strong positive relationship between the return predictive power of any anomalous effect 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 arbitrageurs face higher investment risk and thus higher costs to arbitrage.

Accruals and Asset Growth

Recent research widely examines the viability of simple fundamental-based anomalies such as accruals and asset growth.[3] For the asset growth effect, research findings generally suggest that companies with periods of significant asset expansion or capital expenditures tend to be followed by periods of negative abnormal stock returns. The current research debates whether the asset growth effect can been attributed to mispricing or to systematic risks. On the one hand, the mispricing explanation argues 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 (e.g., Lakonishok, Shleifer, and Vishny (1994)).

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

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[3] Related to asset growth see for instance, Anderson and Garcia-Feijoo (2006), Cooper, Gulen, and Schill (2008), Fama and French (2008), Lyandres, Sun, and Zhang (2008), Polk and Sapienza (2009), Titman, Wei, and Xie (2004), and Xing (2008). For accruals see, for instance, Sloan (1996), Xie (2001), Hribar and Collins (2002), Fairfield et al. (2003), Dechow, Richardson, and Sloan (2008).

[4] For example, the asset growth effect is consistent with investor underappreciation of managerial empire building. As indicated in surveys (Graham, Harvey and Rajgopal [2006]), financial executives are willing to pursue value destructive capital investment activities.

In a seminal article on accruals, Sloan (1996) finds a negative relationship between accruals and subsequent stock returns. In describing the return link, Sloan proposes a mispricing explanation whereby investors overly fixate on earnings in valuing companies. However, investors overestimate the overall persistence of earnings because accruals reverse in subsequent periods and are much less persistent than cash flows. As investors come to recognize their initial estimation error, firms with high (low) levels of accruals generate lower (higher) subsequent stock returns.[5] This mispricing explanation is supported by the corporate finance surveys conducted by Graham, Harvey, and Rajgopal (2006), which 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 also argue that the accrual effect is also attributable to systematic risk.

Our analysis seeks to add insight into whether these two anomalous effects are driven by systematic risks or market mispricing. In order to do so, we further draw on an extensive body of research that explores the importance of limits to arbitrage to investors (e.g., Pontiff (1996, 2006), Shleifer and Vishny (1997), Mashruwala, Rajgopal, and Shevlin (2006)). This literature seeks to understand the impact of arbitrage risk resulting from a lack of close substitutes. Here, arbitrage risk is proxied by IVOL and examines whether greater IVOL reduces investors' ability to realistically eliminate mispricing associated with market anomalies. Should anomalous effects be concentrated in high IVOL stocks, then this finding would lead us towards the mispricing explanation—the anomaly exists due to inability of investors to fully arbitrage away the gains.

[5] As an example, consider the impact of inventory accruals when company managers overestimate sales and, therefore, need to draw down excess inventory in future periods. Another, more sinister, example involves the accounts payable shenanigan of "channel stuffing."

We cannot precisely gauge the extent to which a specific mispricing signal can be arbitraged away. However, by examining the predictive power of the signal and the associated level of IVOL, we can infer the degree to which arbitrageurs are able to exploit the signal. Strong excess returns for a mispricing present in conjunction with high levels of IVOL suggest that it is likely that arbitrageurs have exploited the mispricing signal in a discernible way. As such, the mispricing is accompanied by a lack of close substitutes thus creating important risks to arbitrageurs. We next empirically explore this relationship.

Data and Sample

We obtain financial statement data from the Compustat annual industrial and research files and stock return data from the Center for Research in Security Prices (CRSP) monthly stock returns files for the 1962 through 2008 period. We restrict the sample to all nonfinancial firms with available data and assume a four-month lag after the end of the fiscal year from which we gather the Compustat data items.[6] The final sample is obtained by merging the firms in COMPUSTAT and CRSP that meet all our sample criteria and have non-missing observations for either the accrual or asset growth measures. The final sample period is the 1962 through 2008 period for both accrual and asset growth samples.

For exposition purposes, we follow prior research (e.g., Sloan (1996)) and focus on those firms with fiscal year end in December. We obtain the accrual and asset growth measures available at the end of April and then relate these measures with the subsequent 12 month total returns (inclusive of dividends) from May to April.

[6] Alford, Jones, and Zmijewski (1994) report that the financial statements of almost all firms are publicly available by then.

For delisted firms, the CRSP monthly return file excludes the returns from the delisting month unless the delisting date is at the month end. To create the effective delisting month returns for those excluded firms, we fetch the returns in the delisting month and the market cap on the delisting date from CRSP daily return file and combine these returns with the delisting returns. For stocks whose delisting returns are missing on CRSP, we set the delisting return to -100%.

We measure IVOL as the standard deviation of the residual returns from the Fama-French 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 perform the following time series regression:

$$R_{i,t} - R_{f,t} = a_i + b_i\,(R_{M,t} - R_{f,t}) + s_i\,\mathrm{SMB}_t + h_i\,\mathrm{HML}_t + \varepsilon_{i,t}$$

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

Model and Results

We use monthly Fama-MacBeth (1973) regressions and regress cross-sectionally monthly stock returns during the May-April period on the accrual and asset growth measures calculated with the accounting data for the prior fiscal year. Fama-MacBeth (1973) 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 estimate the following equation:

$$r_{t+1} = a_{0,t} + a_{1,t} Focus\, Factor_t + a_{2,t} Size_t + a_{3,t} BM_t + \varepsilon_{i,t+1} \tag{8}$$

where r_{t+1} is the monthly return; *Focus Factor* represents either the accrual (*ACCRU*) or asset growth (*ASSETG*) measure; *Size* is the logarithm of the equity market capitalization obtained at the end of each April; and *BM* is the logarithm of one plus the book-to-market ratio of equity. Market value of equity is measured at the end of each April and the book equity is the stockholders' book equity (Data216), plus balance sheet deferred taxes and investment tax credit (Data35), minus 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 examine the robustness of our results across the various definitions proposed by the prior literature. As all of our various measures yield similar results, for ease of exposition, we present in the main body of our paper the results for the most straightforward definitions for the two anomaly variables. For *ACCRU*, this definition is the change in net operating assets, and for *ASSETG* we use the annual change in total firm assets. We report the results for the other accrual and asset growth measures in Appendix B. Appendix A provides detailed definitions for all accrual and asset growth related variables. We deflate all the accrual measures with the average total assets over year *t* and *t-1*.

As a first step, we estimate the model for the asset growth and accruals related portfolios as found in the prior literature while extending the study period through 2008. The results are reported in Table 1. Coefficient estimates are the time-series average of coefficient estimates from monthly cross-sectional regressions and the t-statistics are based on the distribution of the monthly coefficient estimates.

[Table 1 here]

Consistent with the prior findings on accruals and asset growth, Table 1 shows that *ASSETG* and *ACCRU* are each inversely related to subsequent returns and are highly significant (at the 1% significance level). The results are also robust when accounting for the size and book-to-market effects. Consistent with Fama-French (1993), book-to-market is positively related with subsequent returns in both models and is significant at the 1% level. Size, however, indicates little significance in either model. In reporting t-statistics, we apply the Newey and West procedure (1987) to correct for potential serial correlation.

We next turn our attention to the main focus of our paper and consider the extent to which arbitrage risks impede investors' ability to arbitrage away the abnormal returns associated with *ACCRU* and *ASSETG* shown in Table 1. For each month we divide our sample into high and low IVOL firms as separated by the median IVOL. We then conduct separate Fama-MacBeth (1973) regressions for each of the two IVOL groups. As discussed earlier, if the accrual or asset growth anomalies are costly to arbitrage, then we would expect their return predictive power to be greater for the sample with higher IVOL. In the extreme case, we may 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 found in Table 1 is largely concentrated among the high IVOL stocks.

[Table 2 here]

In particular, we find that the estimated coefficient for *ASSETG* for high IVOL stocks is -2.68 and is highly significant. But the corresponding estimated coefficient for *ASSETG* for the low IVOL stocks is only -0.03 and is insignificantly different from zero. Furthermore, the t-statistics for the high IVOL group are highly significant with and without controlling for size and book-to-market. In comparison, the corresponding t-statistics for the low IVOL group are insignificant. All together, these findings indicate that the negative association between *ASSETG* and abnormal returns found in Table 1 exists predominantly among those stocks with relatively high IVOL. This suggests that investors attempting to exploit abnormal returns associated with higher asset growth firms will see much higher arbitrage costs and thus face highly uncertain outcomes. IVOL therefore plays an important role in increasing arbitrage costs for investors seeking to arbitrage the *ASSETG* effect. The existence of the asset growth anomaly may, in fact, result entirely from arbitrage risk due to a lack of close substitutes.

We now turn to analyzing the impact of IVOL on accruals. In Panel B of Table 2, we see that the results for the accruals effect bear strong similarity to those for the asset growth effect. The t-statistics are highly significant for *ACCRU* in all models while high IVOL stocks show a considerably higher magnitude of the estimated coefficients for the *ACCRU* characteristic. This suggests that accruals profits are more significantly impacted by the high IVOL group than the low IVOL group. The results are the same when controlling for size and style. These findings indicate that the inverse relationship between *ACCRU* and abnormal returns found in Table 1 is more attributable to those stocks possessing relatively high IVOL. Also, as shown in

Appendix B, we obtain qualitatively the same results for a variety of alternate measures for asset growth and accruals as found in the extant literature.

Because investment practitioners care about more than results, on average, over long periods of time, we now probe more deeply to explore how robust our findings are to the scrutiny of practice. We do so by parsing the framework along a number of key dimensions. In particular, for each anomaly, we form quintile portfolios whereby each stock is ranked and placed into one of five quintiles in accordance with its level of asset growth or accruals characteristic. Quintile 1 (5) corresponds to the quintile firms with the lowest (highest) characteristic. We then run Fama-French (1993) three-factor regressions, which controls for size and style, and a four-factor model with the additional momentum factor of Jegadeesh and Titman (1993). We then report average monthly alphas as sorted by the respective asset growth or accruals 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 associated anomalous 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 choose the sample breakpoint of 1996 as it roughly corresponds to the initial publication date of the accruals anomaly by Sloan (1996). This breakpoint also importantly allocates ample time to each sub-period 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 find that equal-weighted portfolios follow similar patterns.

As discussed below, these more comprehensive results confirm our earlier findings; namely that the largest mispricing for the two anomalies under study can be found among the highest IVOL stocks thereby limiting their effective arbitrage. We now turn our attention to summarizing these more detailed results. For brevity and ease of exposition, we present the results in graphic form for the value weighted three-factor Fama-French (1993) adjusted portfolio results. A comprehensive reporting of our findings can be found in a host of tables in Appendix C.

Figure 1 examines the earlier results from Table 1 by parsing across various periods and quintiles including a spread portfolio, all as described earlier. As expected, the figures demonstrate that the level of alpha is inversely related to both asset growth and accruals, as displayed in Figure 1 Panel A and Panel B, respectively. That is, the level of alpha associated with each anomaly progressively declines with each higher asset growth and accruals quintile, respectively.

Furthermore, as the difference portfolio, represented as "low-high" on each graph, shows both anomalies seemingly present traders with a powerful zero-cost spread portfolio alpha. As detailed in Table C1 in the Appendix, all quintile spread portfolios are significant at the 1 percent level.[8] We'll explore these results in more detail shortly. Finally, the graphs also demonstrate that the associated alphas for both anomalies are highly consistent for the two sub-periods across every quintile suggesting that the anomalous mispricings have not disappeared through time.

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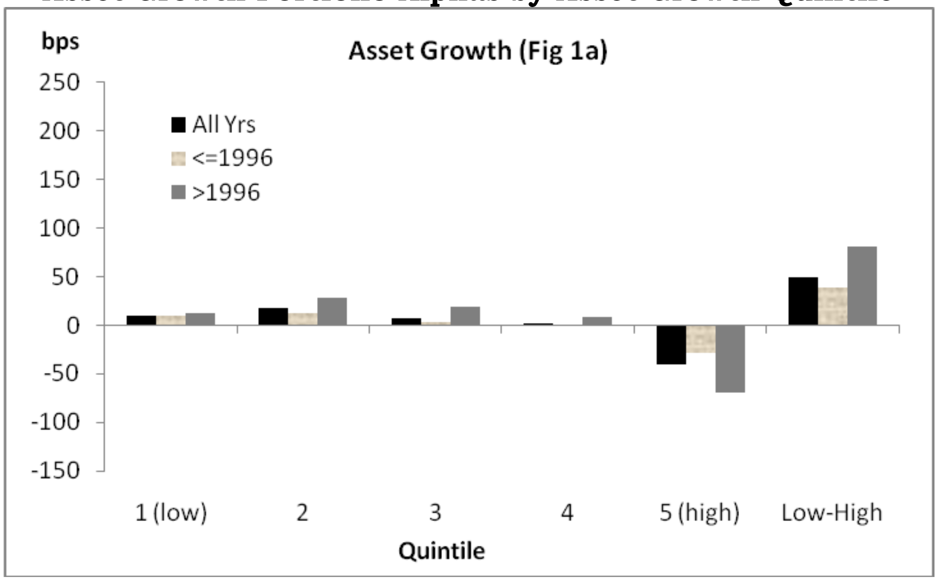
[7] With the use of value-weighted portfolios and annual rebalancing it seems highly unlikely that our findings are meaningfully altered by transactions costs.

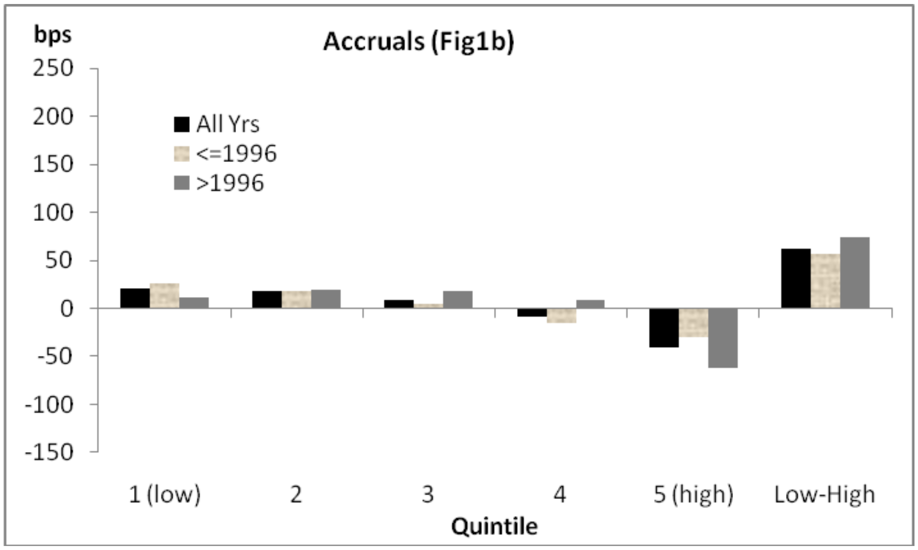
[8] From the coefficient estimate of the difference portfolio adjusted for the Fama-French (1993) three-factors for the 1962-2008 period, we calculate the implied annualized abnormal monthly return as 6.11% (= $(1 + 0.4951\%)^{12} - 1$) for asset growth and 7.76% for accruals.

Figure 1
Three-Factor Alpha Portfolios Sorted by Quintile Portfolios (Value Weighted)
1962-2008

Panel A
Asset Growth Portfolio Alphas by Asset Growth Quintile



Panel B
Accruals Portfolio Alphas by Accruals Quintile



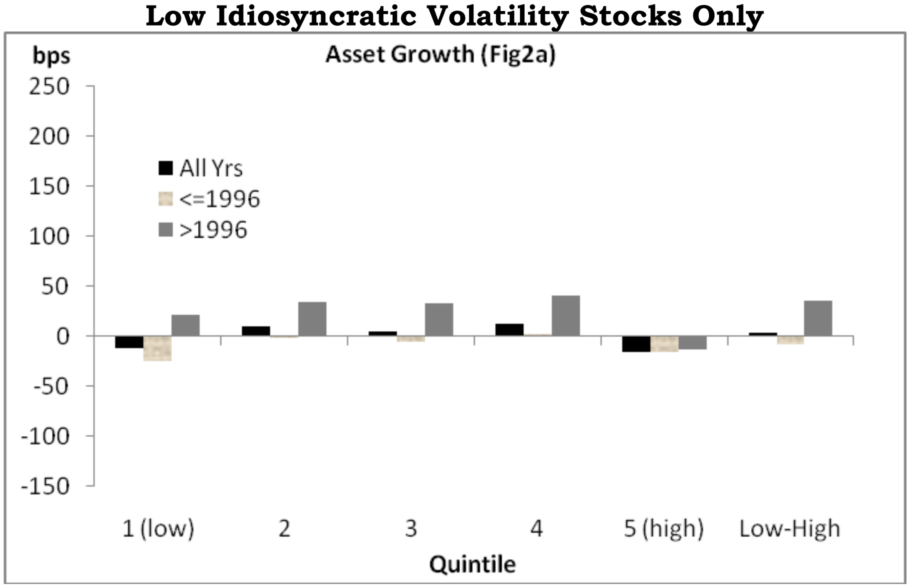
That the anomalous effects persist through time, even after becoming widely known, suggests that some pervasive factor(s) has likely stood in the way of investors in eliminating the effects via arbitrage. Figure 2 presents a more detailed view of the results found in Table 2. In Figure 2, Panel A, we see that the alpha associated with asset growth is weak, and exhibits no discernable pattern for the low IVOL stocks across all asset growth quintiles. Further, as Table C2 in Appendix C shows, the spread portfolio alphas for all three low IVOL periods are statistically insignificant from zero.

In Figure 2, Panel B, we see that the associated asset growth anomaly alpha among the high IVOL stocks for all asset growth quintiles contrasts markedly as compared to the low IVOL stocks shown in Panel A. Contrary to the paltry alphas found within the low IVOL universe, the asset growth anomaly within the high IVOL universe exhibits a highly discernible pattern, moving from a strongly positive alpha in the first quintile of asset growth to strongly negative in the fifth quintile of asset growth. Importantly, for the high IVOL stocks, we point out the large magnitude of the spread portfolio alphas for all three periods, and we note that these alphas are all highly statistically significant.[9]

The three factor quintile alphas associated with the accruals anomaly are shown in Figure 3 and Appendix C2, Panel B. Here, we see that the quintile results for the accruals anomaly bear a strong resemblance to those of the asset growth anomaly from Figure 2 and Appendix C2, Panel A. Perhaps most importantly, again for the accruals anomaly, arbitrageurs, in attempting to extract the statistically significant spread portfolio alpha, must do so among those stocks with higher level of IVOL. The economic significance of the anomalous effect is therefore highly diminished.

Figure 2
Asset Growth Three-Factor Portfolio Alphas Sorted into Asset Growth Quintiles (Value Weighted)
1962-2008

Panel A
Low Idiosyncratic Volatility Stocks Only



Panel B
High Idiosyncratic Volatility Stocks Only

9 This equates to a factor adjusted 21.40% average annualized alpha over the full sample period.

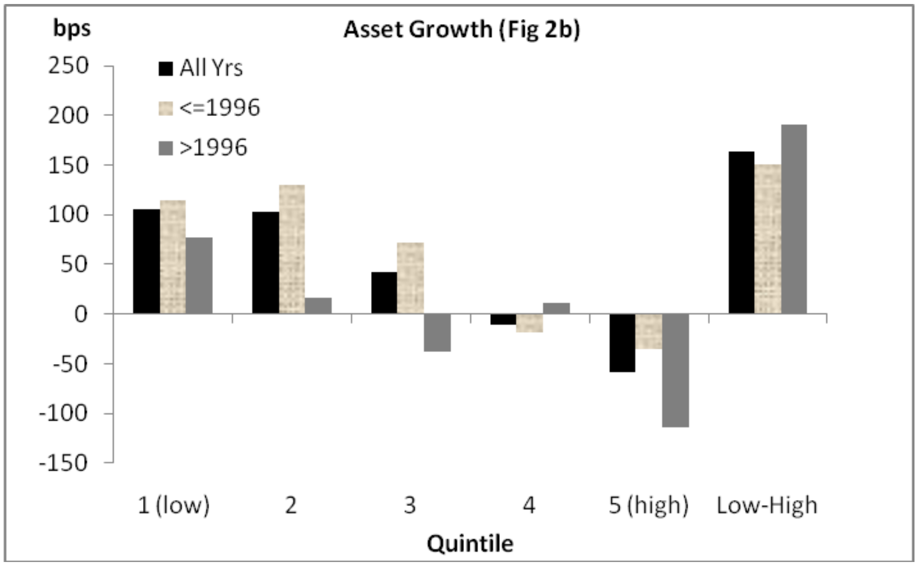
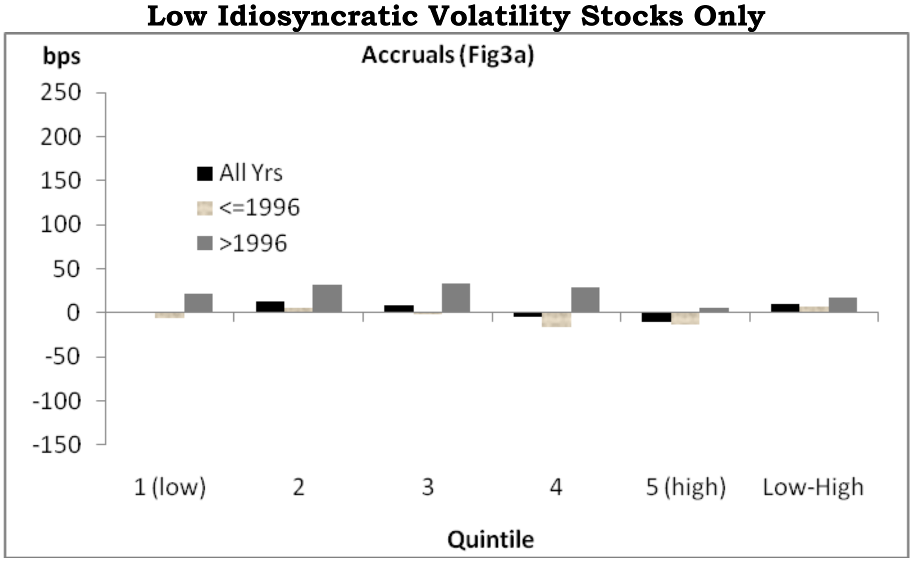
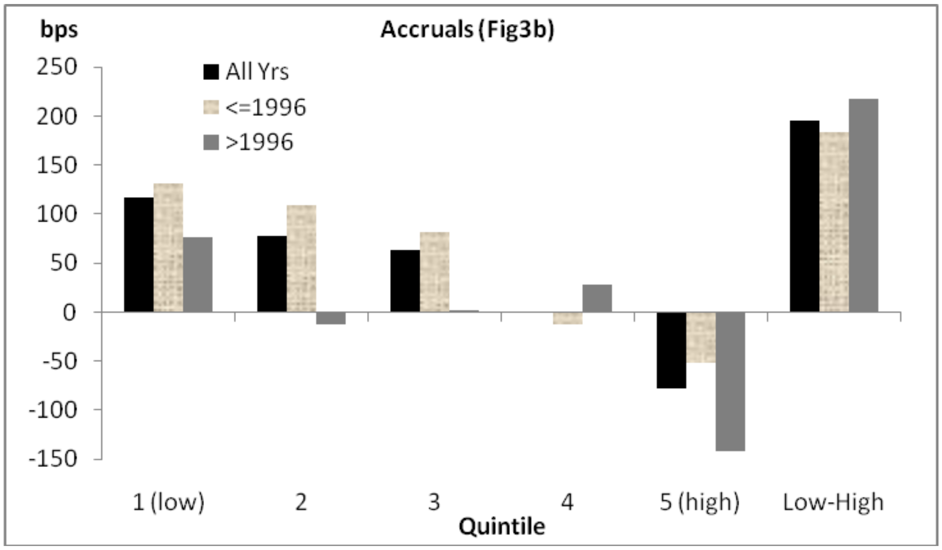


Figure 3
Accruals Three-Factor Portfolio Alphas Sorted into Accruals Quintiles
(Value Weighted)
1962-2008

Panel A
Low Idiosyncratic Volatility Stocks Only



Panel B
High Idiosyncratic Volatility Stocks Only



Taken together, our array of results for both the accruals and asset growth effects support our thesis that investors seeking to profit from abnormal returns associated with long-short portfolios (formed as the difference between high and low quintiles) of accruals and/or asset growth face greater uncertainty. Our evidence suggests that the existence of these anomalous effects found in Table 1 is largely attributable to the arbitrage risk due to the lack of close substitutes thereby hindering their effective profitability.

Conclusion

A central question for informed practitioners involves understanding the extent to which various alpha signals can be effectively used to generate trading profits in the investment process. In a perfect world, the arbitrage risk due to the lack of close substitutes can be completely hedged away; thus any investment signal with a link to excess returns can generate real trading profits. In reality, arbitrageurs are unable to fully hedge away all risks associated with a perfect arbitrage.

Our paper focuses on the risks associated with arbitraging two well-known anomalies: the accrual and asset growth effects. We show that the return link for both effects exist predominantly among stocks with high IVOL suggesting that arbitrageurs face higher arbitrage risk resulting from a lack of close substitutes. The well known accruals and asset growth effects are therefore hard to arbitrage. That is, investors seeking to profit from these two market anomalies must bear substantially higher risks with their trading positions. This risk meaningfully increases the costs to arbitrage away the anomalous effects likely explaining their persistent existence.

We contribute to the extant literature by showing that the arbitrage risk due to the lack of close substitutes creates significant limits to arbitrage for investors to fully reap profits associated with seemingly profitable asset mispricing. Investors may not be able to outperform the market on an after cost basis even if seemingly significant mispricings are identified and persist over time. Most importantly, our paper raises awareness among practitioners of the importance to thoroughly investigate the arbitrage risk from the lack of close substitutes when exploring and implementing alpha signals. Our straightforward methodology could be a useful approach for practitioners to verify the realistic opportunity to profit from an array of identified investment signals.

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Table 1
Cross Sectional Regressions of Firm Returns
Full Sample (1962-2008)

Panel A. Single and Three Variate Regression with Asset Growth

ASSETG	–1.31 ***	–1.32 ***
	–(7.62)	–(7.42)
Size		0.01
		0.70)
BTM		0.67 ***
		(4.76)
Intercept	1.79 ***	1.77 ***
	(7.09)	(6.83)

Panel B. Single and Three Variate Regression with Accruals

ACCRU	–1.35 ***	–1.38 ***
	–(10.74)	–(10.68)
Size		0.01
		(0.43)
BTM		0.69 ***
		(4.78)
Intercept	1.83 ***	1.83 ***
	(7.27)	(7.00)

*** Significant at the 1% level
** Significant at the 5% level

Notes: This table reports the results from Fama-Macbeth (1973) regressions based on the accrual or asset growth measure. Specifically, for each company *i* in year *t* we first estimate factor loadings at the portfolio level, we then assign these loadings to each individual company *i* within the portfolio. This process forms the firm-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 portfolio formation month; *Focus Factor* represents either the accrual (*ACCRU*) or asset growth (*ASSETG*) measure; *Size* is the logarithm of the equity market capitalization obtained at the end of each April; and *BM* is the logarithm of one plus the book-to-market ratio of equity. Market value of equity is measured at the end of each April and the book equity is the stockholders' book equity, plus balance sheet deferred taxes and investment tax credit, minus book value of preferred stock. Coefficient estimates are the time-series average of coefficient estimates from the monthly cross-sectional regressions and the *t*-statistics are based on the distribution of the monthly coefficient estimates. In column two, we report the results for the single focus factor while in column 3 we additionally control for the Fama-French (1992) size and book-to-market effects. Our sample period includes 1962-2008.

Table 2
Cross Sectional Regressions Formed on High and Low Idiosyncratic Volatility
Full Sample (1962-2008)

Panel A. Single and Three Variate Regression with Asset Growth

	IVOL			
	Low	High	Low	High
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)
BTM			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)

Panel B. Single and Three Variate Regression with Accruals

	IVOL			
	Low	High	Low	High
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)
BTM			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)

*** Significant at the 1% level
** Significant at the 5% level

Notes: See notes to Table 1. This table reports the cross sectional regression results whereby the universe of stocks is first divided into either low IVOL or high IVOL firms as separated by the median IVOL.

Appendix A

Definitions of Variables

The data items referred to in this appendix are associated with the Compustat data definitions.

Asset growth measures

ASSETG: the annual change in total firm assets

CGS: (Compustat Data 6, t) / Data 6 (t-1) – 1 from Cooper, Gulen, and Schill (2008), where (Data 6) is the total assets of the firm.

LSZ: [(Compustat Data 3, t) - (Compustat Data 3, t-1) + (Data 7, t) - (Data 7, t-1)] / Data 6 (t-1) from Lyandres, Sun, and Zhang (2008), where (Data 3) is the inventories, (Data 7) is the gross property, plant, and equipment, and (Data 6) is total assets of the firm.

XING: (Compustat Data 128, t) / (Data 128, t-1) – 1 from Xing (2008), where (Data128) is the capital expenditures of the firm.

TWX: (Compustat Data 128, t) / Average(Data 128, t-1, t-2, t-3) – 1 from Titman, Wei, and Xie (2004), where (Data128) is the capital expenditures of the firm.

PS: (Compustat Data 128, t) / (Data 8, 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 firm.

AG: (Compustat Data 128, t) / (Data 128, t-2) -1 from Anderson and Garcia-Feijoo, where (Data128) is the capital expenditures of the firm. (2006).

Accrual measures

ACCRU: change in net operating assets

Δ*NOA* is the change in net operating assets, which is in turn defined as noncash assets less non-debt liabilities ((total assets – cash and short term investments) – (total liabilities – total debt)): ((Data6 - Data1) – (Data181 – *Data9* – *Data34*))

The change in net working capital, which in turn is computed as accounts receivable + inventory – accounts payable – taxes payable + other assets: - (Data302 + Data303 + Data304 + data305 + Data307)

Total Accruals via Cash Flow Statement: Data123 – Data308 – Data311

Current Accruals measured as Net income before extraordinary items – (the change in current assets – the change in current liability): EBITDA-((ACT-ACT1)-(LCT-LCT1))

Appendix B
The Return Predictive Power of Accruals and Asset Growth in Year t+1

See Table 1. This table reports the results from Fama-Macbeth (1973) regressions based on various measures of accruals or asset growth. Column headings are the asset growth or accrual measures as defined in APPENDIX A.

Panel A. Results for various asset growth metrics based on the full sample period.

	TWX		XING		AG		PS		LSZ		CGS	
	1	2	3	4	5	6	7	8	9	10	11	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)		0.70)
Book-to-Market		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 (Cash Flow Statement)		ΔNOA		ΔNet Working Capital		Current Accruals	
	1	2	3	4	5	6	7	8
Accruals	–0.50 **	–0.50 **	–1.35 ***	–1.38 **	–0.45 ***	–0.47 ***	–1.26 ***	–1.26 ***
	–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 ***
		2.51)		0.43)		0.50)		2.77)
Book-to-Market		5.60 ***		0.69 ***		0.65 ***		3.37 ***
		3.28)		4.78)		4.56)		3.39)
Intercept	1.19	1.22 ***	1.83 ***	1.83 ***	1.37 ***	1.35 ***	1.57 ***	1.58 ***
	2.61)	2.62)	7.27)	7.00)	5.53)	5.22)	3.63)	3.56)

Appendix B

Panel B. Results for various asset growth metrics separated by low and high IVOL. Results are based on the full sample period with the universe of stocks divided into either low IVOL or high IVOL firms as separated by the median IVOL.

	TWX				XING				AG			
Volatility	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
	1	2	3	4	5	6	7	8	9	10	11	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)
Book-to-Market			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			
Volatility	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
	1	2	3	4	5	6	7	8	9	10	11	12
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)
Book-to-Market			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)

Appendix B

Panel C. Results for various accruals metrics separated by low and high IVOL. Results are based on the full sample period with the universe of stocks divided into either low IVOL or high IVOL firms as separated by the median IVOL.

	TA (Income Statement)				TA (Cash Flow Statement)				ΔNOA			
Volatility	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
	1	2	3	4	5	6	7	8	9	10	11	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)
Market Cap			-0.03 ***	0.85 ***			-0.03 ***	0.85 ***			-0.05 ***	0.35 ***
			(-6.83)	(6.49)			(-6.88)	(6.39)			(-8.10)	(2.93)
Book-to-Market			-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			
Volatility	Low	High	Low	High	Low	High	Low	High
	1	2	3	4	5	6	7	8
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)
Market Cap			-0.05 ***	0.34 ***			-0.03 ***	0.92 ***
			(-7.98)	(2.76)			(-6.87)	(7.12)
Book-to-Market			-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)

Appendix C
Alpha results for three-factor and four-factor quintile portfolios. Results reported for all years (1962-2008) and for two sub-periods.

Table C1
Monthly Factor-Adjusted Returns of Value-Weighted Quintile Portfolios

In this table, we report average monthly alphas, in basis points, for value-weighted quintile portfolios whereby each stock is ranked and placed into one of five quintiles according to its level of asset growth or accruals characteristic. Quintile 1 (5) corresponds to the quintile firms with the lowest (highest) characteristic as calculated in the prior year. In columns 2 through 4, we report results for Fama-French (1993) three-factor regressions, which controls for size and style, and in columns 5 through 7, we report results for a four-factor model which additionally controls for a momentum factor of Jegadeesh and Titman (1993). We also report the alphas for a zero-cost, spread portfolio, calculated as the difference between the lowest- and highest-ranked quintiles. In addition to the full sample period, 1962-2008, we also report results for two subsample periods, 1962-1996 and 1997-2008.

Panel A. **Asset Growth**

	Three-Factor Model Alphas			Four-Factor Model Alphas		
Rank	Full Sample	Year<=1996	Year>1996	Full Sample	Year<=1996	Year>1996
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)

Panel B. Accruals

Rank	Full Sample	Year<=1996	Year>1996	Full Sample	Year<=1996	Year>1996
	Three-Factor Model Alphas			Four -Factor Model Alphas		
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)

*** Significant at the 1% level
** Significant at the 5% level

Table C2

Monthly Factor-Adjusted Returns of Value-Weighted Quintile Portfolios

See Table C1. This table reports the Fama-French (1993) regression results whereby the universe of stocks is first divided into either low IVOL or high IVOL firms as separated by the median IVOL.

Panel A

	Asset Growth					
Rank	Full Sample	Year<=1996	Year>1996	Full Sample	Year<=1996	Year>1996
	Three-Factor Model Alphas			Four-Factor Model Alphas		
			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)

Table C2

Panel B. Accruals

Rank	Full Sample	Year<=1996	Year>1996	Full Sample	Year<=1996	Year>1996
	Three-Factor Model Alphas			Four -Factor Model Alphas		
			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)
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 *
	(-3.83)	(-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)

*** Significant at the 1% level

** Significant at the 5% level