Unraveling the Asset Growth Effect

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Abstract

Recent papers have argued that the negative correlation between measures of firm asset growth and subsequent returns is either of little importance since it applies only to small firms, justified as compensation for risk, or evidence of mispricing. We show that the asset growth effect is pervasive and evidence to the contrary arises due to specification choices; that one measure of asset growth, the change in total assets, largely subsumes the explanatory power of the numerous other measures; and that the asset growth effect arises from firm growth itself and not from its sensitivity to an asset growth risk factor. We also observe that the ability of asset growth to explain either the cross section of returns or the time series of factor loadings is linked to firm idiosyncratic volatility. In general, there appears to be no asset growth effect in firms with low idiosyncratic volatility. Our findings are consistent with a mispricing-based explanation for the asset growth effect in which arbitrage costs allow the effect to persist.

JEL Classifications: G11; G12; G14

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1. Introduction

An expanding body of research explores the asset pricing implications of changes in firm asset levels. Variously referred to as an "investment effect" and tied to capital investment activity or an "asset growth effect" and tied more broadly to changes in total assets, the underlying empirical regularity is a negative correlation between growth in assets and subsequent returns.[1] The existing literature offers three reactions to this phenomenon. Some argue the effect is unimportant since it is observed only among small firms; some argue the effect is justified since firms with relatively higher asset growth are associated with relatively lower risk; and some suggest the effect is evidence of mispricing. This paper provides a number of tests that address the merits of these arguments and clarify the nature of the asset growth effect.

Out tests contribute to understanding the asset growth effect in a number of ways. First, there is little consensus on how one should measure asset growth and we begin by documenting the manner in which specification choices impact inferences. Second, some papers suggest that the return pattern may be rationally justified based by patterns in risk.[2] For example, Berk, Green and Naik (1999) observe that investment activities convert riskier growth options into less risky assets in place and the reduction in risk justifies the lower return. Another argument arises from q-theory - to the extent that firms make investments when project values rise in response to future discount rates reductions (which in turn must arise as a result of reduced risk), investment

[1] Following the description of the "asset growth effect" in Cooper, Gulen and Schill (2008), if one sorted U.S. stocks based on the percentage change in total assets each June 30th from 1968 to 2006 and sold short an equal-weighting of the top asset growth quintile (mean subsequent annual return of 6.9%) and purchased an equal-weighting of the bottom asset growth quintile (mean subsequent return of 22.6%), the zero investment portfolio would earn a 15.7% mean return. Similar evidence can be found in Fairfield, Whisenant, and Yohn, 2003; Titman, Wei, and Xie, 2004; and Broussard, Michayluk, and Neely, 2005; Anderson and Garcia-Feijoo, 2006; Polk and Sapienza, 2008; Lyandres, Sun, and Zhang, 2008; Xing, 2008.

[2] For example, see Cochrane, 1991, 1996; Berk, Green, and Naik 1999; Gomes, Kogan, and Zhang, 2003; and Li, Livdan, and Zhang, 2008.

activity essentially predicts future risk changes.[3] We consider more explicitly the time series properties suggested by these models. [4] In particular, that relatively higher (lower) investment levels imply a reduction (increase) in risk. Third, based on these same risk arguments, a recent strand of literature has suggested that there exist risk *factors* that are related to asset growth and these factors are being used to explain return anomalies. We evaluate whether the asset growth effect arises due to a priced risk factor or whether it is driven by the underlying firm characteristic. Finally, a number of papers have suggested that the asset growth effect arises from mispricing. For this to be the case, there must exist some limit to arbitrage associated with asset growth, and we evaluate whether the asset growth effect is related to one commonly used measure of arbitrage costs, which is idiosyncratic risk.

We show that the total asset growth measure of Cooper, Gulen, and Schill (2008) largely subsumes the explanatory power of a variety of asset growth measures used in the literature and applies quite strongly to stocks of all sizes. Alternate measures make adjustments to total asset growth or focus on elements of asset growth such as capital expenditures or even the change in capital expenditures. The fact that this single measure dominates others suggests that an emphasis on explanations related to a more restricted measure may be misplaced. Furthermore, asset growth measures that restrict the analysis to portions of total growth generate inferences that may not apply more generally. For example, Fama and French (2008) observe that the negative correlation between the asset growth rate and returns exists only among the smallest

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[3] This argument is based on initial work by Tobin (1969) and Yoshikawa (1980) and elaborated recently in Zhang (2006) and Xing (2007).
[4] Since these models are risk-based explanations, if a proper adjustment for the change in risk were made, then there would be no abnormal returns to a strategy based on asset growth. These models presume that such a risk adjustment cannot be made and that empirical measures based on investments or change in assets, therefore, are observable signals of a change in risk.

capitalization levels.[5] We show that this conclusion arises from the specific definition of asset growth they employ – their measure dampens the asset growth effect by excluding growth that is associated with equity issues, a major source of growth funding for large firms. Another example of sensitivity to specification is the conclusion reached by Anderson and Garcia-Feijoo (2006) and Xing (2009) that the asset growth effect and value effect are closely related. Their tests focus on capital expenditures and not broad growth measures. In our tests, the asset growth effect and the value effect are largely independent and both meaningful and we also demonstrate that the explanatory power of capital expenditures is restricted to smaller firms.

Given the possibility that the asset growth return pattern is related to risk, recent papers suggest there is an underlying risk factor associated with asset growth (Lyandres, Sun, and Zhang, 2007; and Xing, 2007). Following Daniel and Titman (1997), we sort firms based on asset growth and asset growth factor loadings to determine whether the factor loadings on asset-growth are correlated with returns in the cross section. In this manner, we establish whether it is an operating characteristic of the firm (its growth) or a risk factor of the firm (a loading on an asset growth factor mimicking portfolio) that explains returns.[6] We find that even though returns are predictable based on asset growth characteristics, the return patterns do not arise as a result of a systematic priced risk factor. Instead, the effect is related to firm growth itself.

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[5] In particular, they observe that "there is an asset growth anomaly in average returns on microcaps and small stocks, but it is absent for big stocks … that account for more than 90% of total market cap", Fama and French (2008), pp. 1653, 1655.

[6] In effect, this test addresses whether the underlying risk factor is associated with a priced risk premium. The Daniel and Titman (2003) method extends the Fama and MacBeth (1973) methodology. Recent uses of this approach include the Jagannathan and Wang (1996) test of the conditional CAPM, the Brennan, Wang and Xia (2004) test of the intertemporal CAPM, the Canokbekk and Vuolteenaho (2004) test of the two-beta model, and the Core, Guay, and Verdi (2006) analysis of an information risk factor measured by accruals.

Having established the pervasiveness of an asset growth effect and demonstrating that the effect seems to be linked to firm characteristics rather than a firm growth risk factor, the major focus of this paper is to explore the degree to which the asset growth effect is linked to arbitrage costs. In that context we also consider the possibility that the effect arises from changes in the underlying riskiness of the firm (as opposed to being driven by an underlying asset growth risk factor).[7] The asset growth effect could arise from mispricing as follows. If investors over-react to the positive information suggested by higher than anticipated firm growth, future returns will be attenuated as this mispricing unwinds (Lakonishok, Schleifer, and Vishny, 1994). The mispricing explanation, of course, requires some limit to arbitrage or the mispricing would never arise. While we explore the link to a number of arbitrage costs, the focus of our analysis is idiosyncratic volatility, which would be most relevant for effects that occur over long periods of time. For example, Pontiff (2006) suggests that idiosyncratic volatility acts as an important limit to arbitrage in that the greater the realized volatility of a trading position, the less aggressively that position will be pursued by arbitrageurs. Consistent with this interpretation, idiosyncratic volatility has been associated with return anomalies in a number of contexts.[8]

We observe a strong and consistent link between the asset growth effect and idiosyncratic volatility. Specifically, in multivariate Fama-MacBeth style regressions, while asset growth is shown to predict returns, when we include the product of asset growth and idiosyncratic

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[7] For example, see Cooper, Gulen, and Schill (2008) and Polk and Sapienza (2008).

[8] See Baker and Savasogul, 2002 (corporate mergers), Pontiff and Schill, 2004 (equity offerings), and Mashruwala, Rajgopal, and Shevlin, 2006 (accruals). It is true that forming portfolios to trade on these patterns somewhat mitigates idiosyncratic risk, but the portfolios are not sufficiently large that idiosyncratic risk is entirely eliminated. In fact, we find that the idiosyncratic risk of portfolios sorted on firm level idiosyncratic risk is increasing in the average idiosyncratic risk of constituent firms. Taking a ratio of the mean to the standard deviation of the differences in returns across the low and high growth portfolios provides a quasi Sharpe ratio comparison. This value is 0.04, 0.22, 0.34, 0.38, and 0.36, respectively, for the low IVOL to high IVOL quintiles. The values across the top three IVOL quintiles is flat, suggesting that an increase in return comes with a pro-rata increase in idiosyncratic volatility.

volatility, only the product is significant. Furthermore, in bivariate independent sorts (which impose no functional form on the relations) we find that for stocks where idiosyncratic risk is low, there are no reliable differences in returns across extreme portfolios sorted by asset growth. As idiosyncratic risk increases, the returns to high growth portfolios decline, the returns to low growth portfolios increase, and the differences become statistically reliable. Our conclusions are unchanged in series of three-way sorts that control for, among things, firm size. Taken together, these results suggest that the asset growth effect is related to arbitrage costs.

Looking at the time-series of factor loadings for asset growth portfolio returns from a comprehensive 5-factor asset pricing model, the patterns we observe provide weak evidence of increases in factor loadings in event time.[9] Specifically, asset growth portfolios appear to be associated with temporarily larger loadings on some factors after the sorting year, a result consistent with explanations based on changes in risk. However, we find that the increase in factor loadings in the time series exists only among the high idiosyncratic volatility stocks. Moreover, even with time-varying factor loadings in a 5-factor model, the portfolio alphas still manifest a strong abnormal reversal pattern that is consistent with mispricing - the alpha on the low-minus-high growth portfolio return is unusually negative prior to the asset growth sorting date and unusually positive subsequently and then declines to zero. These results indicate that any risk–based explanation would not fully explain the return pattern and, more importantly, such an explanation must also justify the link to idiosyncratic risk.

Our series of tests suggest that the asset growth effect is significant, pervasive, and not a result of an asset growth risk factor. To the extent that idiosyncratic volatility proxies for the

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[9] The risk factors we include are market returns and factor mimicking portfolios of size, book to market, momentum and asset growth.

holding cost associated with arbitrage positions, our analysis provides some evidence of the central role of arbitrage costs in explaining the asset growth effect – a result consistent with explanations for asset growth based on mispricing. As such, our research is closely related to Cooper, Gulen and Schill (2008) and Polk and Sapienza (2008) who document an asset growth effect and provide other evidence consistent with mispricing, but do not document the necessary link to arbitrage costs.[10] Given the observation by Daniel, Hirshleifer and Subramanyam (2001) that the appearance of a positive risk premium might still be observed when the return patterns are generated by mispricing, the link to arbitrage costs is a needed contribution.[11]

Our work draws attention to the burgeoning set of definitions being used to explore this effect and to support various hypotheses. Considering a broad set of such measures, our results suggest that the aggregate growth in assets dominates other measures and is more pervasive across subsamples. As such, our results provide a notable qualification to papers that use more narrow definitions (such as Fama and French (2008), Anderson and Garcia-Feijoo (2006) and Xing (2008)) and suggest that explanations which address the broad and pervasive effect of total asset growth will provide the most robust insights.

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[10] A large number of papers document an effect consistent with a broad asset growth effect but in studies of specific events that lead to increases or decreases in firm size. Such events include acquisitions (Asquith (1983), Agrawal Jaffe, and Mandelker (1992), Loughran and Vijh (1997), Rau and Vermaelen (1998)), public equity offerings (Ibbotson (1975), Loughran and Ritter (1995)), public debt offerings (Spiess and Affleck-Graves (1999)), bank loan initiations (Billet, Flannery, and Garfinkel (2006)), and broadly defined external financing (Pontiff and Woodgate (2006) and Richardson and Sloan (2003)), spinoffs (Cusatis, Miles, and Woolridge (1993), McConnell and Ovtchinnikov (2004)), share repurchases (Lakonishok and Vermaelen (1990), Ikenberry, Lakonishok, and Vermaelen (1995)), debt prepayments (Affleck-Graves and Miller (2003)), and dividend initiations (Michaely, Thaler, and Womack (1995)). Notably, Cooper,Gulen and Schill (2008) demonstrate that the asset growth effect is not a manifestation of these specific events, but a general phenomenon.

[11] In the context of mispricing that unwinds over time, a trading cost related to the holding period, such as idiosyncratic risk, is the relevant cost. Transaction-related costs would be of lesser importance. Consistent with this distinction, we find little relation between the asset growth effect and measures of transaction-related trading costs.

Our work is also related to that of Lyandres, Sun, and Zhang (2007) and Xing (2007), who make use of asset growth based factors to explain return patterns. We find that loadings on such factors provide little ability to explain the cross-section of returns and that it is the asset growth characteristic that explains returns rather than any asset growth risk factor loading.[12] Our results suggest the explanatory power of these factors in the Lyandres, Sun, and Zhang (2007) and Xing (2007) papers may actually arise from firm characteristics and mispricing rather than from a true risk factor.

The rest of the paper is organized as follows. Section 2 simplifies the understanding of the many manifestations of the asset growth effect. Section 3 examines the degree to which asset growth may function as a risk factor. Section 4 provides tests of the limits to arbitrage with a focus on the role of idiosyncratic risk. Section 5 examines the time series properties of factor loadings. Section 6 provides concluding remarks.

2. The asset growth effect

Our sample is composed of all nonfinancial firms (one-digit SIC code not equal to 6) with data available on Compustat annual industrial files and CRSP monthly files. To mitigate backfilling biases, a firm must be listed on Compustat for two years before it is included in the dataset (Fama and French, 1993). As in Fama and French (1992), we consider returns from July of the sorting year through June of the following year, using Compustat annual financial

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[12] Lyandres, Sun, and Zhang (2008) create an investment factor (long in low-investment stocks and short in high-investment stocks) and use that factor to explain the abnormal returns to firms expanding due to stock and equity issuance. Xing (2008) also shows that the asset growth effect diminishes the book-to-market effect and attributes the result to implications of q-theory. As noted in Daniel, Hirshleifer and Subramanyam (2001), the explanatory power of these factors does not preclude the possibility they arise from mispricing and these papers simply document that explanatory power.

statement information from fiscal year ending by at least December 31 of the year prior to the sorting year.

2.1 Exploring the variety of asset growth-style definitions

We define seven measures of asset growth: CGS, the total asset growth rate as defined by Cooper, Gulen, and Schill (2008); FF, the share-adjusted asset growth rate from Fama and French (2008); LSZ, the investment-to-asset ratio from Lyandres, Sun, and Zhang (2008); XING, the growth rate in capital expenditures from Xing (2008); TWX, the firm capital expenditures divided by the average capital expenditures over the past three years from Titman, Wei, and Xie (2004); PS, the ratio of capital expenditures to net property, plant, and equipment from Polk and Sapienza (2008); and AGF, the firm capital expenditures divided by capital expenditures two years previous from Anderson and Garcia-Feijoo (2006). Each of these measures is defined in detail in the appendix.

We construct size and book-to-market ratio measures for each firm. For firm size, we use the market value of the firm's equity from CRSP at the end of June of the sorting year. For the book-to-market ratio (BM), we use market value from December of the year prior to the sorting year. Book value of equity is as defined in Davis, Fama, and French (2000) where book equity (BE) 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). Values for these variables are obtained for years 1968 to 2006.

Table 1 provides the time-series averages for annual median values and correlation coefficients across these variables over the sample period from 1968 to 2006. The average median firm size as measured by equity capitalization is $83 million, the average median book-to-market ratio is 0.74, and the average median growth rates range from 6.7% to 21.5% across the different measures. The distribution of each of these measures is highly skewed. For this reason, when estimating correlation coefficients or performing regression analyses we transform the values by taking the natural logarithm of the value plus 1. The correlation coefficient between size and the asset growth measures range from -0.02 to 0.16. All of the measures are negatively correlated with the book-to-market ratio as recognized by Anderson and Garcia-Feijoo (2006) and Xing (2008). The correlation coefficient between the book-to-market ratio and the asset growth measures range from -0.12 and -0.29. As expected by the commonality in the accounts used in their construction, the various asset growth measures are strongly correlated. Average correlation coefficients range from 0.34 for the FF and XING measures to 0.88 for the TWX and AG measures. Those measures based on growth rates in assets (CGS, FF, and LSZ) share a particularly strong correlation, and so do those measures based on growth rates in capital expenditures (XING, TWX, PS, and AGF).

To provide some evidence of the relation between these measures and subsequent stock returns, we report the mean equal-weighted and value-weighted returns associated with portfolios formed on these measures. In Panel B we provide the equal-weighted returns for portfolios formed on the basis of market capitalization, the book-to-market ratio, and the seven asset growth measures. Panel C provides the value weighted returns. In comparing the extreme quintiles we observe significant differences in all asset growth sorts, on both an equal and value weighted basis. The low-minus-high quintile return differences range from 0.7 to 1.3 percent a month for the equal-weighted portfolios and from 0.4 to 0.7 percent for the value-weighted portfolios.

To control for interdependent effects across the firm characteristics we turn to Fama and MacBeth (1973) type regressions to explain cross-sectional variation in monthly returns. Based on the time series of monthly regression coefficients, our inference uses the t-tests of the mean coefficient, corrected for serial correlation. These results are tabulated in Table 2. In our baseline regression (Regression 1), we regress returns on log of size, and log of 1+ book-to-market. We find, consistent with previous work, and our portfolio results in Table 1, that size is generally negatively related to returns, and book-to-market is positively related to returns.

We now add each of the seven asset growth measures in turn to the right-hand side of the regression. These results are reported in Regressions 2 through 8. We find that all of the measures of asset growth are significantly negatively related to returns with large t-statistics ranging from -3.60 to -9.09. The test results demonstrate the striking negative correlation between asset growth measures and subsequent returns.

Anderson and Garcia-Feijoo (2006) and Xing (2008) suggest a link between asset growth the book-to-market ratio. Using their measure, they observe that book-to-market is subsumed by the growth effect. When we add the asset growth variables to our baseline specification, the coefficient on book-to-market declines somewhat from 0.003 (t-statistic=3.81) to the lowest value of 0.002 (t-statistic=2.92) with the CGS asset growth measure. The effect is similar for the explanatory power of size. In all cases, the asset growth rate measure fails to subsume the explanatory power of the book-to-market or size effects. Our results are not intended to directly refute the work of Anderson and Garcia-Feijoo (2006) and Xing (2008) – there are some differences in our specifications – but it is important to recognize the asset growth effect, in whatever measurement, remains strong when book-to-market is included and that in our sample the two effects are independent.

Since our measures of growth are all strongly correlated with each other as reported in Table 1, we next propose to simplify the empirical analysis by testing whether one asset growth measure subsumes the other measure's ability to explain returns. In effect we test whether there are several "asset growth effects" or just one. To do this, we add the measure with the highest t-statistic from the return regressions, the CGS measure, to each of the specifications. Since some of the asset growth measures (TWX and AGF) are estimated over multiple years we also include the twice lagged value of the one year CGS measure for these specifications. These results are reported in Regressions 1 through 6 of Panel B of Table 2. Adding the CGS measure to the regression has a modest effect on the coefficient of CGS and a dramatic effect on the coefficient on the other asset growth measures. For the FF effect, the coefficient estimate reverses sign to now be positive and significant with the t-statistic switching from -6.24 to 3.04. The addition of the CGS total asset growth measure drives out the explanatory power of most of the other value measures. The t-statistics drop from -7.54 to -0.91 for the LSZ measure, from -5.93 to -2.15 for the XING measure, from -5.86 to -1.05 for the TWX measure, from -3.60 to -0.38 for the PS measure, and from -5.70 to -1.54 for the AGF measure. In each of these specifications the explanatory power of the CGS measure is strong with t-statistics ranging from -6.90 to -9.41. The coefficient on the twice-lagged value of the CGS measure is also highly significant with t-statistics ranging from -2.07 to -2.92 in the two specifications that include this measure. For all but the XING measure, the alternative measures of asset growth no longer maintain any explanatory power. While the t-statistic for the XING measure drops from -5.93 to -2.15, the t-statistic on the CGS measures drops from -9.09 to -8.62 when both measures are included in the same regression. Later in the section, we review the residual explanatory power of the XING measure in portfolio tests. In the Panel B regression results, the CGS measure largely subsumes the explanatory power of the other measures. This empirical relation between asset growth measures and stock returns is remarkably simple—the cross-section of returns is strongly negatively correlated with total changes in the size a firm's balance sheet.

To further demonstrate the empirical relations across the various asset growth measures, we perform various decompositions. We begin with the Fama-French measure which is defined as

$$\text{FF} = \frac{Assets\ (t)}{Split-adjusted\ \ shares\ outstanding\ \ (t)} \div \frac{Assets\ (t-1)}{Split-adjusted\ \ shares\ outstanding\ \ (t-1)} \qquad (1)$$

and can be rearranged alternatively to

$$\text{FF} = \frac{Assets\ (t)}{Assets\ (t-1)} * \frac{Split-adjusted\ \ shares\ outstanding\ \ (t-1)}{Split-adjusted\ \ shares\ outstanding\ \ (t)}. \qquad (2)$$

The alternative expression of the Fama-French measure is the product of two measures. The first term is simply the CGS total asset growth measure. The second term is the inverse of the growth rate is shares outstanding. This is the measure used by Pontiff and Woodgate (2006) that has been shown to be negatively correlated with subsequent returns. By effectively multiplying the CGS measure by the inverse of the Pontiff-Woodgate measure, the Fama-French measure dampens the explanatory power of the CGS measure. Since the regressions used log-transformed values, we can easily split the FF measure into the two additive terms. We alter the regression specification of Panel A for the Fama-French measure by decomposing the FF measure into the two components: CGS and Pontiff-Woodgate. This specification is reported in Regression 7 of Panel B. The coefficient on both the CGS and Pontiff-Woodgate measures are negative and highly significant, as expected. The CGS measure maintains significant explanatory power but this does not subsume that of the growth in shares outstanding documented by Pontiff and Woodgate. As an additional test of the explanatory power of CGS and PW among large-capitalization stocks as stressed by Fama and French, we weight the Regression 7 specification by market capitalization. This value-weighted regression is reported in Regression 9. The coefficient estimates for both CGS and PW are significant in a value-weighted set up with t-statistics of -3.43 and -3.56, respectively. Thus, in contrast to the conclusion in Fama-French, asset growth explains returns even among large cap stocks.

The Lyandres, Sun, Zhang (LSZ) measure is identical to the CGS measure except that the numerator is based on the change in inventory and gross PP&E rather than based on changes in total assets. To test for the explanatory power of the residual assets not included in the LSZ measure we compute a residual measure (CGS-LSZ) which is simply the difference between the CGS measure and LSZ measure. We include this residual measure as a regressor with the LSZ measure in Regression 8. We observe that the coefficient on LSZ and CGS-LSZ are negative, significant, and close in magnitude. The coefficient on LSZ is -.012 (t-stat=-6.92) and the coefficient of CGS-LSZ is -0.10 (t-stat=-6.91). The results suggest that the correlation structure between returns and asset growth is just as strong among inventory and PPE growth as it is for growth in other line items of the balance sheet.

Regression 4 shows that the XING measure maintained some significant unique explanatory power in the cross-section. As an additional test of the explanatory power of XING, we value-weight the cross-sectional regression that includes both XING and CGS. We report the results in Regression 10. We see that the CGS measure maintains its statistical significance while the XING measure does not. It appears the explanatory power of the XING measure is not strong among large cap stocks.

To further explore the interrelation between the CGS and XING measures we perform independent five-by-five annual sort of stocks based on CGS and XING. These sorts are the same ones reported in Table 1. We form 25 portfolios based on the intersection of the sorts and compute monthly returns. These mean returns are reported in Panel A of Table 3. We also report the mean return for the position that is long the low growth quintile and short the high growth quintile. We observe that the low-minus-high spread across the CGS measure is economically large and statistically significant across all XING quintiles. Monthly spread returns levels range from 0.97% to 1.35% with t-stats that range from 5.44 to 6.87. For the XING portfolios, we observe that the spread returns are substantially smaller, ranging from -0.02% to 0.42% and that the statistics are only significant for the extreme CGS quintiles. Firms with either high or low total asset growth also generate capital expenditure growth effects (XING) but not those with more moderate total asset growth. In summary, the XING/capital expenditure effect appears to be isolated to small-cap stocks and to stocks with extreme asset growth.

This section provides an empirical analysis that greatly clarifies and simplifies the correlation structure between the many measures of asset growth and subsequent returns. Since it appears that the CGS measure largely subsumes the explanatory power of returns on the other measures of asset growth, we focus on the CGS measure as our proxy for the firm asset growth rate in many of the remaining tests in the paper.

2.2 *Is the asset growth effect economically material?*

Fama and French (2008) claim that the asset growth is not economically material as it only exists among small cap stocks. In particular, they claim that the effect does not exist among the stocks that comprise 90% of the wealth of the market.

With our added understanding of the differences between FF and CGS measure in the previous section, we construct a test which compares the Fama and French results across the two measures. We begin by replicating a result in the Fama and French paper by performing independent sorts by market capitalization and the FF measure. Following Fama and French, we establish three size breakpoints based on the annual 20% and 50% NYSE size percentiles. Firms below the 20% break point are denoted as "Micro." Firms between the 20% and 50% break point are denoted as "Small." Firms above the 50% break point are denoted as "Big." The average portfolio returns from these sorts are reported in Panel B of Table 3. The test results are similar to the findings of Fama and French in that the asset growth is smaller among the large capitalization stocks, however we do find that the spread is greater than that in the Fama and French sample.[13]

In Panel C, however, we alter the asset growth sorts to be based on the CGS measure rather than the FF measure. Although we continue to observe a decline of the effect among large capitalization stocks, the effect is certainly strong and statistically significant among this group. The mean asset growth spread is 0.67% per month for the Big stocks with a t-statistic of 4.04. We conclude that the asset growth generates a very material effect across stocks in that it is pervasive across stocks that are material in the economy. The distinction between the two

[13] One important change in the Fama and French sample and that used in this paper is that Fama and French eliminate from their sample all firms with negative book-to-market ratios.

findings is based on the definition of the measures and in particular the dampening effect caused by the per-share normalization. One way to reconcile the findings is establishing that a primary way for large cap firms to finance large balance sheet expansions is through equity issuance. Removing share issuance from the total asset growth rate maintains a particularly important effect on large-cap stocks.

3. Does asset growth generate a systematic risk premium?

The use of zero-cost portfolio returns has become an accepted way to capture common return sensitivity (e.g., Fama and French, 1993). Daniel and Titman (1997) emphasize that the return premia associated with loadings on such factors are consistent with both risk-based and characteristic-based explanations. Lyandres, Sun, and Zhang (2008) propose an investment factor based on the investment-to-asset ratio. Xing (2008) proposes an alternative investment factor based on investment growth rates. Although they argue that these factors are theoretically motivated by q-theory, they recognize that their results are also consistent with simple measures of systematic mispricing across firm asset growth characteristics. In effect, our goal in this section is to differentiate these two explanations.

Regardless of whether the factor captures systematic risk or mispricing, we might expect that cross-sectional loadings on the factor to be positively correlated with returns. For example, if we sort portfolios on book-to-market, high book-to-market firms will have a higher factor loading on the *HML* portfolio, and low book-to-market firms will have a lower factor loading. It is known that high book to market firms yield higher future returns, and the low book to market firms yield lower future returns. If the factor loadings on book to market are positively correlated with this portfolio characteristic, the factor loadings will then, similar to returns from book to market portfolio sorts, produce a positive relation between factor loadings and returns, which would be interpreted as a risk premium.

We begin by constructing three asset growth factors based on zero-cost portfolio returns. The construction of the first two growth factors follows the investment-to-asset ratio factor (INV) proposed Lyandres, Sun, and Zhang (2008) and the investment growth factor (IGR) proposed by Xing (2008). We form a third measure in a similar manner based on the LGS asset growth measure. We denote the third factor as *GRO*. We form each of the asset growth factors by first sorting portfolios independently into growth and NYSE-size terciles as of the end of June of year t. We get 9 portfolios for each of the three asset growth measures. We then average each of the asset growth portfolios across the size terciles, to obtain three growth portfolios that are independent from size. We difference the extreme portfolios sorted on asset growth in order to calculate the zero-cost return portfolios.

We form the HML and SMB factor mimicking portfolios in an identical manner using NYSE book-to-market and size terciles, so as to form book-to-market portfolios that are independent from size, and size portfolios that are independent from book-to-market. Following Daniel and Titman (1997), portfolios are resorted every year, but we keep the composition of all portfolios constant during the estimation period, using portfolio weights as of June 30^{th} of year t, which allows for better predictions of future factor loadings.

We first establish that the growth factor (and the related investment factors of Lyandres, Sun, and Zhang (2007) and Xing (2007)) generate "risk" premiums. We then follow Daniel and Titman (1997) and test whether the driver of this explanatory power is actually the factor loading (a true risk premium) or the underlying firm characteristics (not a risk premium).

The general approach is to construct factor loadings from the time series of returns (regress returns over time on the factor mimicking portfolios). We then sort based on the factor loadings and measure the degree to which the loading is then related to returns from those sorts. In other words, we evaluate whether the cross-section of loadings is, in fact, related to the cross-section of returns. If so, then the return difference reflects the risk premium associated with the given factor. Looking at each of the three growth factors in Table 4, Panel A, we find that the loadings on the three measures generate marginally significant differences in returns across the loading quintiles with a return premium for the high investment factor loading portfolio over the low investment factor loading portfolio with t-stats of 1.99 for INV, 1.54 for IGR, and 1.93 for GRO.

In the subsequent panels, we evaluate whether the factor loading or the respective underlying firm characteristic better explains the cross section of returns. We do this with two-way sorts. We sort based on the factor loadings and on the underlying growth characteristic (asset growth (CGS), investment-to-assets (LSZ), or investment growth (XING)). If the return patterns are associated with mispricing generated by firm growth, then we would expect firm growth to better explain returns than the factor loadings. Looking at the results in Table 4 for INV (Panel B), IGR (Panel C), and GRO (Panel D), we find that controlling for factor loading, the firm asset growth characteristic is significantly correlated with returns. In most cases the difference in returns across the high growth and low growth firm returns is highly significant. This is not the case for the variation in loadings. We find that controlling for firm characteristic, it is rare for the factor loadings to be priced at a significant level. We conclude that it is the firm growth characteristics that are correlated with returns rather than a sensitivity to a common growth factor as suggested in the literature.

4. Are high arbitrage costs necessary for the asset growth effect?

With such a large return premium, the asset growth effect is bound to attract arbitrage attention. To evaluate how such an effect can persist in equilibrium, we turn to a test using the cross-section of firm arbitrage costs. Similar arbitrage cost tests have been used by others to explore mispricing using other return effects (see Pontiff, 1996 (closed-end funds); Ali et al., 2003 (value effect); Lesmond, Schill, and Zhou, 2004; McLean, 2009 (price momentum and reversal). The costly arbitrage explanation employs the standard arbitrage logic that in a frictionless world if a security is undervalued (overvalued) then arbitrage traders costlessly buy (sell) the undervalued (overvalued) security and costlessly sell (buy) a fair-priced security that is perfectly correlated with the fundamental value of the mispriced security. Arbitrage traders costlessly hold the position until prices reflect fundamental values. The standard finance conclusion is that such arbitrage trade pressure eliminates mispricing. In a world of trading frictions, however, the incentive to eliminate mispricing may be diminished because the expected cost of initiating, holding, and terminating the position may exceed the expected benefits.

Pontiff (2006) separates arbitrage costs into two types, transactions costs and holding costs. Transaction costs are defined as those costs that are proportional to acts of initiating and terminating arbitrage positions. Transaction costs may include such trading frictions as bid-ask spreads, market impact, and commissions. Holding costs are defined as those costs that are proportional to the amount of time the arbitrage position is held. Holding costs may include such frictions as interest on margin requirements, short sale costs (e.g., the haircut on short sale rebate rate) and the risk exposure of maintaining a position with idiosyncratic volatility when the arbitrageur has difficulty in finding a good hedge. The focus of this paper is, of course, a return effect that occurs over long periods of time (Cooper, Gulen, and Schill (2008) estimate that the effect continues for up to five years and generates return differentials of more than 80%). The holding costs would, therefore, be expected to play a prominent role with transaction costs being less important or possibly irrelevant. We include both to highlight this distinction and to control for any transaction cost effect.

4.1 Transaction costs

We consider three transaction cost measures. We use the Gibbs sampler estimate of the Roll (1984) bid-ask spread cost measure proposed by Hasbrouck (2006). The Roll measure estimates bid-ask spreads from the time series of daily price changes based on the magnitude of the negative serial correlation in returns. Since returns are often positively correlated, implying a negative spread, Hasbrouck (2006) proposes a Gibbs sampler estimate of the Roll measure that minimizes this problem. Using direct measures of spreads as benchmarks, Hasbrouck finds that the Gibbs sampler estimate of the Roll model is the best measure of effective trading costs. We obtained the estimates of the Gibbs sampler estimate from Joel Hasbrouk. We denote this measure *GIBBS*. We do not use measures of quoted or effective spreads because of the lack of necessary high frequency data which are only available for a relatively short time series. The indirect measures we use are available for a significantly longer period and allow us to analyze a more comprehensive sample.

We use the price impact measure proposed in Amihud (2002) that is calculated as the ratio of the absolute value of the daily stock return to its daily dollar trading volume. Since volume on Nasdaq is known to be overstated as a result of trades between dealers, we divide volume on Nasdaq-listed firms by 2 (see Atkins and Dyl (1997)). We annualize the measure by taking the simple average of the daily measure. We denote this measure *AMIHUD*. Since

AMIHUD is the daily price response associated with one dollar of trading volume, it serves as an indicator of price impact (See Hasbrouk, 2006).

We use a measure of total transaction costs proposed by Lesmond, Ogden and Trzcinka (1999), and denote this measure *LOT*. The premise of their model is that the marginal investor only trades when the value of the information signal is high enough to exceed the costs of trading, otherwise the security experiences a zero return. In effect, their model estimates the effective transaction cost of the marginal trader. Our LOT estimates were provided by David Lesmond. It should be noted that GIBBS, AMIHUD and LOT are all measures of trading costs and thus are inverse measures of liquidity.

4.2 Holding costs and idiosyncratic volatility

Pontiff (1996, 2006) argues that idiosyncratic volatility is an important measure of holding costs. A number of papers demonstrate the importance of idiosyncratic volatility empirically in explaining mispricing (see Baker and Savasogul, 2002 (corporate mergers); Pontiff and Schill, 2004 (equity offerings); Mashruwala, Rajgopal, and Shevlin, 2006 (accruals)). In effect, the idiosyncratic risk exposure of the mispriced security is important to arbitrageurs because positions in that security are difficult to hedge. Pontiff (1996) argues that arbitrageurs trade off the degree to which they profit from predictable return patterns against the degree of risk they incur to do so – and that risk is increasing in the magnitude of firm specific idiosyncratic risk. We discuss this argument, which is central to our analysis, in detail below.

Pontiff (2006) asserts that arbitrageurs' preference for mispriced assets is sensitive to the idiosyncratic volatility of the asset. Arbitrageurs prefer to hold assets with lower idiosyncratic volatility for any level of expected abnormal return. In practice, the arbitrageur has two alternative ways to reduce the idiosyncratic volatility in the arbitrage portfolio: he can increase the number of assets in the portfolio or underweight assets with high idiosyncratic volatility. A simple example illustrates the portfolio math.[14]

Suppose arbitrageurs hedge market risk following Pontiff (2006) such that returns on a position in asset *i* can be represented as

$$r_i = a_i + r_f + e_i \tag{3}$$

where a_i is an asset specific constant, r_f is the risk-free rate, and e_i is the idiosyncratic noise in returns with variance equal to σ_i^2. Suppose that the arbitrageur observes *M* assets with $a > 0$ and *N* assets with $a_i < 0$. The arbitrageur's expected return on a strategy that is long in the *M* assets and short in the *N* assets is equal to $\bar{a}_L - \bar{a}_S$ where $\bar{a}_L$ is the weighted average return on the *M* underpriced assets and $\bar{a}_S$ is the weighted average returns on the *N* overpriced assets. The variance of the long-short portfolio return is equal to

$$\sigma_p^2 = \frac{\bar{\sigma}_L^2}{M} + \frac{\bar{\sigma}_S^2}{N} \tag{4}$$

where $\bar{\sigma}_L^2$ and $\bar{\sigma}_S^2$ represent the weighted average variance for the long and short portfolios, respectively. Since the noise term is idiosyncratic, there is by definition no covariance terms in the portfolio variance equation.

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[14] We thank Bruce Grundy for his help in articulating this example.

As a simple numerical example, suppose that the number of long and short assets is 100 (M=N=100) and the portfolio variance for both positions is 0.5 per year ($\bar{\sigma}_L^2$ = $\bar{\sigma}_S^2$ = 0.5). Substituting these values into Equation 2 and taking the square root we find that the standard deviation of the long-short portfolio return is 10%. If the expected abnormal return $\bar{a}_L - \bar{a}_S$ is also 10% per year, the arbitrage position maintains a return over risk Sharpe ratio of 1. To reduce the standard deviation of the portfolio return by half, the arbitrageur can either increase the number of assets from 100 to 400 or decrease the weighted average idiosyncratic volatility from 0.5 to 0.25. Because of this trade-off, in the cross-section of arbitrage opportunities the idiosyncratic volatility of an asset will matter to the arbitrageur.

Following past literature we define idiosyncratic volatility as the standard deviation of the residuals from a regression of daily returns on an equal-weighted market index over a minimum of 100 days starting from July 1 through June 30 of the present year (*IVOL*). Although this measure only excludes market risk, we find that our results are insensitive to many alternative measures of idiosyncratic volatility. This insensitivity is due to the relative magnitudes of firm-specific return variance and factor variance. In effect the magnitude of firm-specific variance dwarfs the variance of standard factors.

4.3 Regressions

We now return to our cross-sectional regression framework and add our measures of arbitrage costs as well as variables that interact the arbitrage costs with the firm asset growth rate to identify whether the asset growth effect is explained by arbitrage costs. If the asset growth effect is consistent with costly arbitrage, then we expect the relation between asset growth and returns to be greater when arbitrage costs are high and smaller when arbitrage costs are low. Specifically, we expect the interaction variable to have a negative coefficient.

Our results are reported in Table 5. As a reference, Regression 1 of Table 5 repeats from the specification of Regression 2 of Table 2 (the regression documenting the explanatory power of the asset growth effect). We note again that the t-statistic on the CGS asset growth measure is -9.09. In Regression 2 of Table 5 we add *IVOL* and *IVOL* interacted with the asset growth rate. We find that the interaction coefficient with *IVOL* is statistically significant. The coefficient on the interaction with asset growth and IVOL is -0.260 [t-statistic=-3.87]. Thus, our results suggest that the asset growth effect increases significantly with our proxy for holding cost. In fact, the coefficient on the asset growth rate becomes insignificant with the inclusion of the IVOL interaction - the coefficient becomes -0.008 [t-statistic=-0.48], suggesting that the asset growth effect exists only when in conjunction with idiosyncratic volatility. Furthermore, the coefficient on idiosyncratic volatility is insignificant, suggesting that idiosyncratic volatility is not independently priced. In tests unreported in the table we find that IVOL maintains no significant explanatory power when the interaction term is excluded.[15]

In Regressions 3, 4, and 5 we consider the explanatory power of the three transaction cost estimates GIBBS, AMIHUD, and LOT in a similar manner to IVOL. In these regressions, we find that he AMIHUD measure is positively related to returns, which is consistent with a role as a transaction cost, but the other variables are insignificant. Thus, as expected, there is little evidence that returns measured over the time period studied are related to transaction costs. As for the interaction between these measures and asset growth, the only notable effect is with the

[15] Our results on the predictive power of idiosyncratic volatility differs from the work of Ang et al. (2006) but is consistent with Bali and Cakici (2008).

GIBBS measure. The significant negative coefficient suggests there is some relation between asset growth and this measure and it is of the sign expected if transaction costs were able to explain the asset growth effect. However, once again, if we consider all the transaction cost measures there is little evidence of this effect. In fact, when we include all the transaction measures together with IVOL in regression 6, only IVOL shows a relation to asset growth. Thus, the results in Table 3 document a link between IVOL and asset growth that is consistent with an arbitrage cost explanation.[16]

As in the Table 2 regressions, the regressions in Table 5 include a book-to-market measure and firm size. As in Table 2, the book-to-market effect continues to be significant in all our specifications, once again suggesting that the asset growth effect is independent of the book-to-market effect. The inclusion of firm size is of particular importance in the Table 5 regressions since it might be argued that any relation between returns and idiosyncratic volatility may just be a reflection of firm size. In our results, there is a size effect, though it is diminished when transaction cost measures are included. More importantly, the explanatory power of idiosyncratic volatility interacted with asset growth exists even with size in the regressions.

4.4 Portfolio return tests

The cross-sectional regressions in the previous section impose a defined structure on the relation between returns and characteristics. An alternate approach is to look at portfolios sorted on the characteristics, so that no such structure is assumed. We sort the stocks into five portfolios based on the asset growth rate and report summary statistics (means of annual median values) for these portfolios in Table 6. These sorts are the same ones performed and reported for CGS in

[16] Ali et al. (2003) establish a similar relation between idiosyncratic volatility and the book-to-market effect.

Tables 1 and 3. For the asset growth rate sort, the asset growth rate varies from -14.9% for the low growth group to 57.5% for the high growth group. To provide further detail on the characteristics of the firms within each of the five portfolios, we report the average annual median size and book-to-market ratio across the groups. The low growth group tends to be fairly small ($30 million) and have high book-to-market ratios (0.99). The size peaks in portfolio 4 ($167 million) and the book-to-market ratio is lowest in portfolio 5 (0.45). It is again clear that firm asset growth is correlated with the book-to-market ratio as suggested by Anderson and Garcia-Feijoo (2006) and Xing (2008).

From Table 6 we observe that both extreme asset growth portfolios are associated with higher arbitrage costs, but particularly the low growth firms. Median monthly idiosyncratic volatility over the past year ranges from 23.3% for the low asset growth group to 13.0% for the middle growth group to 16.3% for the high growth group. The *GIBBS* measure ranges from a high 1.5% spread for the low asset growth group to a 0.5% spread for the middle growth group to a 0.7% spread for the high growth group. The *AMIHUD* price impact measure ranges from a high 4.2 for the low asset growth group to 0.3 for the middle growth group to 0.4 for the high growth group. The LOT measure follows a similar pattern.

Table 1 reports the associated mean monthly portfolio returns for the groups over the year subsequent to the June 30th sorting date (July to June of the next year). The portfolio return values monotonically decline with the increase in firm expansion from 1.9% for the low growth group to 0.6% for the high growth group. The 1.31% difference in monthly gross returns (15.7% per year) for the asset growth rate sorts are highly statistically significant. The only arbitrage cost measures that we can directly compare with returns are the GIBBS and LOT measures. If we add the two mean GIBBS values for the extreme asset growth portfolios we obtain 2.2% for the asset growth rate sort. This sum is an estimate of the mean round-trip bid-ask spread cost from buying and selling a position in portfolios 1 and 5 and rebalancing the entire position every June 30th. A similar calculation for the LOT measure produces a mean total round-trip transaction cost estimate of 12%. Both transaction cost estimates are smaller than the mean low-high arbitrage return of 15.7%.

Table 6 also reports the median idiosyncratic volatility estimate over the subsequent 12 months. We note that the estimates are generally of the same magnitude: low growth firms generate IVOL values of 23.3% before and 21.7% after sorting while the high growth firms generate IVOL values of 16.3% before and 16.5% after sorting. There does not seem to be dramatic change in firm IVOL in event time. It is curious to note that the IVOL of the high growth firms tends to modestly decline and the IVOL of the high growth firms tends to modestly rise (both are statistically significant despite being small in magnitude). This tendency is the opposite of what is predicted if time-series in idiosyncratic risk explains the trends in returns in a "pricing of risk" framework.

We now turn to investigating the interaction of the asset growth effect with other firm characteristics in double-sorted portfolios. We start by studying the relations between book-to-market, size, and asset growth effects. Berk, Green and Naik (1999) suggest that the book-to-market and size effects are driven by changes in risk caused by changes in the firm's investment opportunities set. In their model, firms realize investment opportunities as they invest, and because growth opportunities are riskier than assets in place, risk declines as firms invest and transform growth opportunities into assets in place. Assuming high investment firms have low book-to-market ratios, i.e., high investment opportunities, and are smaller, then the book-to-market and size effects documented in Fama and French (1992) should be explained by this asset growth effect. Anderson and Garcia-Feijoo (2006) conclude that the book to market and asset growth effects are the same, and therefore the book-to-market effect can be explained by the theoretical framework of Berk, Green and Naik. Xing (2008) observes similar effects.

In order to investigate to the independence of these effects we compute portfolio returns for portfolios of firms sorted independently into quintiles based on the lagged book-to-market and size measures with respect to our asset growth rate and investment-to-asset ratio quintiles. We compute monthly portfolio returns from July of the sorting year through June of the following year. The mean portfolio returns are reported in Table 7 for book-to-market ratio (Panel A) and size (Panel B). To observe the interactions of the effects, we focus our attention on the difference in returns between the extreme portfolios, controlling for the alternative characteristic. If the asset growth effect subsumes the book-to-market and size effects, as suggested by some risk-based models, we expect the difference in returns across book-to-market ratio or size quintiles to disappear once these values are conditioned on the asset expansion quintile. We find that this is not the case.[17] At all levels of asset growth rate, the difference in returns is highly significant across the extreme quintiles for both the book-to-market ratio and firm size. Thus, size and book-to-market effects persist after sorting on asset growth, a result again inconsistent with the conclusions of Anderson and Garcia-Feijoo, and Xing. In Panel A, the differences in monthly returns between the high and low book-to-market ratio quintiles are 1.0%, 1.0%, 0.7%, 0.7%, and 1.2% across asset growth rate quintiles 1 through 5, respectively. There is no evidence that the book-to-market disappears once firm investment policy is

[17]To reconcile our result with that of Xing, we repeat our portfolio tests using the Xing measure. In these tests we observe results similar to Xing, the book-to-market effect is diminished with the change in capital expenditures although the differences in quintile returns in our tests are still significant.

considered. High book-to-market ratio stocks generate 1.2% higher monthly returns than low book-to-market ratio stocks, even among the sample of firms that are growing assets at an average rate of 57% (see Table 6). Moreover, the asset growth effect is also robust to controlling for size and book-to-market levels. The difference in returns between extreme asset growth rate portfolios is almost identical across the five book-to-market quintiles. We do observe a relationship with size (the asset growth effect is smaller among larger firms) as already observed by Cooper, Gulen, and Schill (2008) and Fama and French (2008), but in both cases the difference in returns across asset growth groups is still significant among the largest quintile stocks at 0.7% [t-stat=3.90]. We note that these results are consistent with the cross-sectional regressions in the previous section.

Our principal objective in this section is to explore the link between arbitrage costs and returns. We therefore construct sorts of asset growth against arbitrage measures. In the cross-sectional return regressions, we noted the importance of idiosyncratic volatility and we shall see the same once again. We now conduct the two-way sorts for asset growth relative to measures of arbitrage costs: *IVOL* (Panel C), *GIBBS* (Panel D), *AMIHUD* (Panel E), and *LOT* (Panel F). We observe some increasing asset growth effect relationship across arbitrage cost quintiles that is particularly strong with *IVOL*. The return difference on the extreme asset growth quintiles is just 0.1% (t-stat of 1.02) for the low IVOL stocks and increases monotonically to 1.7% per month (t-stat of 7.47) for the high IVOL stocks. It appears that the asset growth effect is particularly strong among high *IVOL* stocks and nonexistent among low *IVOL* stocks. The firm characteristic IVOL maintains the most important correlation with the asset growth effect.

While the advantage of portfolio sorts is their lack of assumptions regarding the functional form of relations, a disadvantage is their limited ability to control for other effects. Of particular concern in this instance would be the lack of a control for firm size, but other controls should also be addressed – such as the book-to-market effect and transaction costs. To accommodate additional controls, one can increase the number of sorts. However, one quickly runs into problems with the size of samples in each partition. While the regressions already establish that the IVOL effects we document survive in the face of other effects, we provide some additional evidence in the form of three-way sorts reported in Table 8.

To allow for sufficient sample sizes in the three-way sorts in Table 8, we employ tercile sorts of the variables of interest. The table itself presents the difference between the high and low terciles for asset growth portfolios after first sorting on IVOL and one other variable. In particular, we control for the book-to-market effect, firm size, the GIBBS measure of transaction costs, the AMIHUD measure of transaction costs, and the LOT measure of transaction costs in panels A, B, C, D and E, respectively. If the median number of stocks in any three-way sorted portfolio is less than 10, we do not report the portfolio return. The results are again striking in the relation with IVOL. Controlling for the other variables, we note that in every case, we see that the asset growth effect continues to be increasing in the degree of idiosyncratic volatility.

To further understand the effect of IVOL on asset growth portfolios, we present summary statistics on IVOL portfolios in Table 9. Specifically, we present for each IVOL quintile time series statistics on portfolio returns for low asset growth, high asset growth and portfolios that are long on low and short on high asset growth portfolios. For each quintile of IVOL, monthly returns for the difference between the low and high asset growth portfolios ranges from 0.1% to 1.7% as shown previously in Table 7. We observe that the standard deviation of the difference portfolio is increasing with IVOL, and almost doubles from 2.5% per month for the lowest IVOL portfolio to 4.7% per month for the highest IVOL portfolio. Taking a ratio of the mean to the standard deviation of the differences in returns across the low and high growth portfolios provides a quasi Sharpe ratio comparison. This value is 0.04, 0.22, 0.34, 0.38, and 0.36, respectively, for the low IVOL to high IVOL quintiles. The values across the top three IVOL quintiles is flat, suggesting that an increase in return comes with a pro-rata increase in idiosyncratic volatility. We also observe that asset growth portfolios do experience some inherent risk with the 25th and 75th percentile monthly returns being about the same amount above and below zero. For example, among high IVOL stocks the 25th percentile return is -2.1% while the 75th percentile return is 2.1%. As with standard deviation, this gap increases with IVOL. These results suggest that investors are not able to diversify away idiosyncratic volatility when forming portfolios that take advantage of the asset growth effect.

The results of the portfolio sorts confirms the results in the cross-sectional regressions – that the asset growth effect does not completely subsume the book-to-market effect and, more important, appears to be limited to those stocks with high idiosyncratic volatility.

5. Time-series effects

As a last set of tests we examine the time-series characteristics of stock risks (factor loadings) and alphas over the five years prior to, and subsequent to, the sorting year. The goal is to evaluate how a standard asset pricing model reflects the change in risk implied by the risk-based explanations of the asset growth effect.

In Figure 1 we plot the intercept and 5-factor model loadings using the returns for the respective event year of low asset growth, high asset growth and zero-investment portfolio formed by taking a long position in the low asset growth portfolio and a short position in the high asset growth portfolio. We observe a substantial reversal pattern in the intercept of the difference portfolio consistent with Cooper, Gulen, and Schill (2008). The magnitude of the intercept over several years after the sorting year suggests that our crude dynamic risk adjustment model with five factors does little to diminish the magnitude of the raw return differential discussed in the introduction to this paper, even when directly controlling for an asset growth factor. If time-varying loadings are to explain the abnormal returns, we might expect the various loadings to increase after the sorting year. We find no evidence of an increase for the market or SMB loading. There is some evidence that the loading on the zero-cost portfolio increases for HML, MOM, and GRO, but this increase is fleeting.

To further understand the temporary increase in factor sensitivity, we partition the asset growth quintiles by idiosyncratic risk quintiles as in the analysis reported in Table 4. We repeat the estimation procedure across the event window, for the low minus high asset growth zero-investment portfolios sorted by idiosyncratic volatility quintiles. In Figure 2, we plot the coefficients on the difference portfolio for each of the two extreme IVOL quintiles. Examining the plot of the intercept, we observe that the time-series reversal in the abnormal return (alpha) is concentrated among the high IVOL stocks. We also observe that the temporary increase in loadings is restricted to high IVOL stocks. These figures suggest that an explanation of the asset growth effect based on time variation in risk factors must also maintain a role for idiosyncratic volatility.

6. Conclusions

There are conflicting conclusions regarding the nature of the asset growth effect in stock returns. Some argue the effect is immaterial, some argue the effect is justified by variation in priced risk, and some suggest it arises from the correction of mispriced securities. This paper provides a series of tests to improve the understanding of the role of asset growth in stock returns. We find that the asset growth effect is highly economically material as it is strong among large cap stocks. We observe that the asset growth effect is not captured in a common risk factor. Violations of market efficiency that may be implied by mispricing would challenge the fundamental function of markets. Of course, mispricing need not violate market efficiency if the mispricing exists within reasonable arbitrage bounds. We investigate exactly what constitutes those bounds and what they can tell us about return patterns. In particular, we look at arbitrage costs and the return patterns for the asset growth effect.

We find that firm idiosyncratic volatility, our measure of the arbitrage costs necessary to sustain mispricing, is a necessary condition for asset growth effects both in the cross section of returns and the time series patterns in factor loadings and that a factor mimicking portfolio based on asset growth does not generate a risk premium once firm growth is acknowledged. It appears that no matter how we cut the data, firm idiosyncratic risk plays a prominent role in explaining the cross-section and the time-series variation in asset growth returns. We conclude that arbitrage costs are a necessary condition for the existence of the return patterns we examine. In particular, large holding costs that we model with estimates of idiosyncratic volatility create frictions to exploiting these patterns. Our results suggest that the return patterns in asset growth are most consistent with the effects of costly arbitrage.

Appendix. Definitions of asset growth measures

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

CGS measure: (Compustat Data 6, t-1) / Data 6 (t-2) – 1 from Cooper, Gulen, and Schill (2008), where (Data 6) is the total assets of the firm.

FF measure: the log ratio of assets per split-adjusted share at t-1 divided by assets per split-adjusted share at t-2 following Fama and French (2008). Assets per split-adjusted share outstanding at the fiscal yearend in t-1 is computed as follows: Log{ (Compustat Data 6, t-1) / [(Compustat Data 25, t-1)* (Compustat Data 27, t-1)] }

LSZ measure: [(Compustat Data 3, t-1) -- (Compustat Data 3, t-2) + (Data 7, t-1) - (Data 7, t-2)] / Data 6 (t-2) 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.

PS measure: (Compustat Data 128, t-1) / (Data 8, t-2) from Polk and Sapienza (2008), where (Data128) is the capital expenditures and (Data 8) is the net property, plant, and equipment of the firm.

XING measure: (Compustat Data 128, t-1) / (Data 128, t-2) – 1 from Xing (2008), where (Data128) is the capital expenditures of the firm.

AGF measure: (Compustat Data 128, t-1) / (Data 128, t-3) -1 from Anderson and Garcia-Feijoo, where (Data128) is the capital expenditures of the firm. (2006).

TWX measure: (Compustat Data 128, t-1) / Average(Data 128, t-2, t-3, t-4) – 1 from Titman, Wei, and Xie (2004), where (Data128) is the capital expenditures of the firm.

PW measure: Growth in split-adjusted shares outstanding based on Pontiff and Woodgate (2008) where split-adjusted shares outstanding are defined as (Compustat Data 25, t-1)*(Compustat Data 27, t-1).

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Table 1. Summary Statistics

This table reports averages of the annual median values and the average annual correlation coefficient for the various firm characteristics of US stocks over the 1968 to 2006 period. The variables are: Size, the market value of equity as of June 30; the book-to-market ratio (BM) as defined in Davis, Fama, and French (2000) where the market value is of December of the previous year and the book value of equity is the stockholders' book equity (Compustat data 216), plus balance sheet deferred taxes and investment tax credit (Compustat data35), minus book value of preferred stock (in the following order: Compustat data56 or data10 or data130) of the previous year; CGS (Asset growth), the percentage change in total assets from Cooper, Gulen, and Schill (2008); FF, the ratio of assets per split-adjusted share at the fiscal yearend divided by assets per split-adjusted share at the previous fiscal yearend following Fama and French (2008), LSZ, the investment-to-asset ratio from Lyandres, Sun, and Zhang (2008); XING, the growth rate in capital expenditures from Xing (2008), TWX, capital expenditures divided by the average capital expenditures over the past three years from Titman, Wei, Xie (2004), PS, the ratio of capital expenditures to net property, plant, and equipment from Polk and Sapienza (2008), and AGF, capital expenditures divided by capital expenditures two years previous from Anderson and Garcia-Feijoo (2006). To minimize the effect of outliers, we winsorize the data at the 1% and 99% levels. For the correlation coefficient estimates we log transform all variables. Because asset growth rate measures can take negative values we add one before taking the logs.

Panel A. Summary Statistics of Firm Characteristics

			Asset growth rate measures						
	Size	*BM*	*CGS*	*FF*	*LSZ*	*PS*	XING	*AG*	*TWX*
Mean	83.0	0.74	0.079	0.057	0.067	0.214	0.095	0.215	0.106
Correlation coefficients									
Size	1.000	-0.262	0.138	0.163	0.122	-0.016	0.095	0.095	0.110
Book-to market ratio (BM)		1.000	-0.256	-0.196	-0.187	-0.288	-0.122	-0.166	-0.183
Cooper-Gulen-Schill (CGS)			1.000	0.823	0.702	0.486	0.385	0.417	0.467
Fama-French (FF)				1.000	0.591	0.387	0.340	0.360	0.408
Lyandres-Sun -Zhang (LSZ)					1.000	0.495	0.400	0.445	0.494
Polk-Sapienza (PS)						1.000	0.547	0.610	0.748
Xing (XING)							1.000	0.627	0.731
Anderson-Garcia-Feijoo (AGF)								1.000	0.884
Titman-Wei-Xie (TWX)									1.000

Table 1. Summary statistics (Continued)

Panel B. Mean equal-weighted returns

			Asset growth rate measures						
Quintile	*Size*	*BM*	*CGS*	*FF*	*LSZ*	XING	*TWX*	*PS*	*AG*
1 (Low)	0.013	0.006	0.019	0.016	0.017	0.016	0.017	0.016	0.016
2	0.010	0.011	0.016	0.016	0.016	0.014	0.014	0.014	0.015
3	0.010	0.013	0.014	0.014	0.014	0.013	0.014	0.014	0.013
4	0.010	0.015	0.012	0.012	0.012	0.012	0.012	0.012	0.012
5 (High)	0.009	0.018	0.006	0.007	0.007	0.009	0.009	0.009	0.009
Low - High	0.003	-0.012	0.013	0.009	0.010	0.007	0.008	0.008	0.007
(t-stat)	1.656	-6.448	8.416	6.083	8.643	7.008	6.624	5.076	6.383

Panel C. Mean value-weighted returns

			Asset growth rate measures						
Quintile	*Size*	*BM*	*CGS*	*FF*	*LSZ*	XING	*TWX*	*PS*	*AG*
1 (Low)	0.011	0.007	0.013	0.011	0.013	0.011	0.010	0.011	0.011
2	0.010	0.010	0.011	0.011	0.011	0.011	0.011	0.011	0.011
3	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
4	0.010	0.011	0.009	0.009	0.008	0.009	0.009	0.009	0.009
5 (High)	0.009	0.013	0.006	0.007	0.006	0.004	0.006	0.006	0.005
Low - High	0.002	-0.006	0.007	0.004	0.007	0.006	0.004	0.006	0.006
(t-stat)	0.829	-3.199	4.113	2.505	4.759	4.050	2.574	2.230	3.659

Table 2. Cross-sectional regressions of firm returns

This table reports cross-sectional regressions of monthly returns on various firm characteristics of US stocks over the period 1968 to 2006. Coefficient estimates are time series averages of cross-sectional regression coefficients, obtained from monthly cross-sectional regressions. The independent variables are defined in Table 1. CGS (t-2) is the CGS asset growth measure lagged an extra year. To minimize the effect of outliers, we log transform and winsorize the independent variables at the 1% and 99% levels except returns. In parentheses are t-statistics robust to serial correlation, and ** denotes significance at the 1% level, * at the 5% level.

Panel A.

	1	2	3	4	5	6	7	8
Intercept	0.020**	0.020**	0.020**	0.021**	0.017***	0.019**	0.020**	0.019**
	(4.11)	(4.28)	(4.12)	(4.27)	(3.2)	(4.04)	(4.11)	(4.06)
BM	0.003**	0.002**	0.003**	0.003**	0.002***	0.003**	0.003**	0.003**
	(3.81)	(2.92)	(3.49)	(3.29)	(3.47)	(3.60)	(3.43)	(3.29)
Size	-0.001*	-0.001*	-0.001*	-0.001*	-0.001**	-0.001*	-0.001*	-0.001*

	(-2.43)	(-2.17)	(-2.18)	(-2.26)	(-2.35)	(-2.25)	(-2.26)	(-2.14)
Asset growth rate measures								
CGS		-0.012**						
		(-9.09)						
FF			-0.008**					
			(-6.24)					
LSZ				-0.014**				
				(-7.54)				
PS					-0.002**			
					(-3.60)			
XING						-0.002**		
						(-5.93)		
AGF							-0.002**	
							(-5.70)	
TWX								-0.002**
								(-5.86)

Table 2. Cross-sectional regressions of firm returns (Continued)
Panel B.

	1	2	3	4	5	6	7	8	9	10
	EW	EW	EW	EW	EW	EW	EW	EW	VW	VW
Intercept	0.021***	0.020***	0.020***	0.020***	0.021***	0.020***	0.021***	0.020***	0.015***	0.015***
	(4.41)	(4.27)	(3.79)	(4.23)	(4.4)	(4.39)	(4.46)	(4.26)	(3.20)	(3.42)
BM	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.001	0.001
	(2.92)	(2.91)	(3.04)	(2.91)	(2.74)	(2.64)	(2.90)	(2.91)	(1.40)	(1.24)
Size	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.000	-0.0003
	(-2.28)	(-2.15)	(-2.11)	(-2.07)	(-2.09)	(-2.01)	(-2.33)	(-2.17)	(-0.80)	(-0.82)
CGS	-0.016***	-0.011***	-0.012***	-0.012***	-0.011***	-0.011***	-0.010***		0.008***	0.010***
	(-8.74)	(-6.90)	(-9.41)	(-8.62)	(-9.15)	(-9.01)	(-7.34)		(-3.43)	(-4.76)
CGS (t-2)					-0.003**	-0.003***				
					(-2.07)	(-2.92)				
FF	0.006***									
	(3.04)									
LSZ		-0.002						-0.012***		
		(-0.91)						(-6.92)		
PS			-0.000							
			(-0.38)							
XING				-0.001**						-0.0005
				(-2.15)						(-0.84)
AGF					-0.000					
					(-1.54)					
TWX						-0.000				
						(-1.05)				
PW							-0.007***		-0.01***	
							(-3.28)		(-3.56)	
CGS-LSZ								-0.010***		
								(-6.91)		

Table 3. Portfolio returns based on two-way independent sorts

Panel A. CGS and XING asset growth rate sorts

		CGS Asset growth rate						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
XING	1(low)	1.99%	1.61%	1.43%	1.16%	0.87%	1.13%	6.69
	2	1.85%	1.56%	1.36%	1.25%	0.71%	1.15%	6.87
	3	1.66%	1.50%	1.32%	1.15%	0.69%	0.97%	5.44
	4	1.98%	1.51%	1.43%	1.14%	0.62%	1.35%	6.28
	5 (high	1.69%	1.55%	1.24%	1.18%	0.45%	1.24%	5.97
	Low - high	0.30%	0.06%	0.19%	-0.02%	0.42%		
	[t-stat]	2.13	0.48	1.63	-0.16	2.82		

Panel B. FF asset growth rate and size sorts

		FF Asset growth rate						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
Size	Micro	1.82%	1.77%	1.61%	1.39%	0.74%	1.09%	7.34
	Small	1.03%	1.33%	1.29%	1.16%	0.60%	0.43%	3.05
	Big	0.95%	1.16%	1.16%	1.04%	0.71%	0.25%	1.71

Panel C. CGS asset growth rate and size sorts

		CGS Asset growth rate						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
Size	Micro	2.03%	1.74%	1.54%	1.33%	0.65%	1.37%	9.40
	Small	1.26%	1.36%	1.34%	1.10%	0.49%	0.77%	5.19
	Big	1.27%	1.23%	1.13%	1.03%	0.59%	0.67%	4.04

Table 4. Portfolio returns based on independent sorts with investment factor loadings

This table reports value-weighted mean monthly portfolio returns for portfolios of stocks formed at the end of June from 1968 through 2006. Panel A presents mean portfolio returns based on quintile sorts on the investment factor loadings of GRO, INV, and ING. We also present portfolio returns based on independent sorts of asset growth (CGS) with investment factor loadings GRO (Panel B), the investment-to-asset ratio (LSZ) with investment factor loadings INV (Panel C), the growth rate in capital expenditures (XING) with investment factor loadings ING (Panel D). Investment factor loadings are estimated with a four factor model for each firm-year with rolling regressions ending in December of the year prior to the sort and starting 36 months before. Loadings are estimated using a regression of firm monthly excess returns on the three Fama and French factors and on one of the three investment factors. The table presents results for two-way independent sorts based on these variables into quintiles. Portfolios are rebalanced annually. Portfolios returns are from the beginning of July of the sorting year through the end of June of the following year. For each month, we take the difference in portfolio return for the extreme quintiles. Over the sample period there are 468 monthly observations (12 months x 39 years of data). The t-statistics for the extreme quintile spreads are reported in brackets with ** denoting significance at the 1% level, and * at the 5% level.

Panel A. Portfolio returns formed on factor loading sorts

		Factor definition		
		INV	IGR	GRO
Loading on investment factor	1(low)	1.0%	1.00%	1.0%
	2	1.0%	1.00%	1.0%
	3	1.2%	1.10%	1.1%
	4	1.1%	1.10%	1.2%
	5 (high)	1.3%	1.30%	1.4%
	High-low	0.4%	0.30%	0.4%
	[t-stat]	[1.99*]	[1.54]	[1.93]

Panel B. Portfolio returns formed on LSZ growth rate and loading on INV

		LSZ						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
Loading on investment factor INV	1(low)	1.5%	1.2%	1.2%	0.9%	0.8%	0.7%	[3.18**]
	2	1.3%	1.2%	1.1%	0.9%	0.8%	0.6%	[2.88**]
	3	1.5%	1.2%	1.2%	1.2%	1.0%	0.5%	[2.97**]
	4	1.5%	1.3%	0.9%	1.0%	1.1%	0.4%	[2.20*]
	5 (high)	1.5%	1.4%	1.4%	1.3%	1.0%	0.5%	[2.13*]
	High-low	0.0%	0.1%	0.2%	0.4%	0.2%		
	[t-stat]	[-0.12]	[0.56]	[0.72]	[1.62]	[0.87]		

Table 4. Portfolio returns based on independent sorts with investment factor loadings (Continued)

Panel C. Portfolio returns formed on XING growth rate and loading on IGR

		XING						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
Loading on investment factor IGR	1(low)	1.3%	1.4%	1.1%	1.0%	0.6%	0.7%	[3.36**]
	2	1.3%	1.1%	1.1%	0.9%	0.8%	0.4%	[1.92]
	3	1.5%	1.2%	1.1%	1.1%	1.0%	0.5%	[2.50*]
	4	1.0%	1.1%	1.0%	1.0%	1.0%	-0.0%	[0.16]
	5 (high)	1.3%	1.4%	1.2%	1.5%	1.0%	0.3%	[1.07]
	High-low	0.0%	0.0%	0.2%	0.5%	0.4%		
	[t-stat]	[-0.09]	[0.14]	[0.72]	[2.01*]	[1.60]		

Panel D. Portfolio returns formed on CGS growth rate and loading on GRO

		CGS						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
Loading on investment factor GRO	1(low)	1.3%	1.5%	1.1%	0.9%	0.8%	0.5%	[2.45*]
	2	1.4%	1.2%	1.1%	1.0%	0.7%	0.7%	[4.36**]
	3	1.5%	1.2%	1.0%	1.2%	0.8%	0.7%	[4.59**]
	4	1.5%	1.3%	1.1%	1.0%	1.1%	0.4%	[2.42*]
	5 (high)	1.7%	1.5%	1.4%	1.1%	1.2%	0.5%	[3.07**]
	High-low	0.4%	-0.1%	0.3%	0.2%	0.4%		
	[t-stat]	[2.17*]	[-0.41]	[1.75]	[1.08]	[1.77]		

Table 5. Cross-sectional regressions of firm returns with arbitrage cost proxy variables

This table reports monthly cross-sectional regressions of monthly returns on various firm characteristics of US stocks over the period 1968 to 2006. Some of the independent variables are defined in Table 1. Asset growth is defined as the annual change in total assets divided by the lagged value of total assets. Idiosyncratic volatility (IVOL) is defined as the standard deviation of the residuals of a market model regression of firm returns over the twelve months prior to sorting. The Gibbs illiquidity measure (GIBBS) is the Gibbs sampler estimate of the Roll (1984) model over the calendar year prior to the sorting year. The Amihud illiquidity measure (AMIHUD) is the Amihud (2002) measure of illiquidity calculated using stock returns and trading volume over the prior twelve months. To facilitate reporting, in this table we multiply AMIHUD by 1000. The Lesmond, Ogden and Trzcinka (1999) measure of transaction costs (LOT) is calculated from daily stock returns over the calendar year prior to the sorting year. To minimize the effect of outliers, we log transform and winsorize the data at the 1% and 99% levels except returns and arbitrage cost measures. Because asset growth rate measures can take negative values we add one before taking the logs. Coefficient estimates are time series averages of cross-sectional regression coefficients, obtained from monthly cross-sectional regressions. In brackets are t-statistics, and ** denote significance at the 1% level, * at the 5% level.

	1	2	3	4	5	6
Intercept	0.020**	0.018**	0.016**	0.017**	0.016**	0.018**
	(4.28)	(6.46)	(3.32)	(3.51)	(3.76)	(5.92)
BM	0.002**	0.003**	0.002*	0.003**	0.002**	0.002**
	(2.92)	(3.94)	(2.38)	(2.93)	(3.19)	(2.61)
Size	-0.001*	-0.001**	-0.001	-0.001	-0.001	-0.001
	(-2.17)	(-2.70)	(-1.04)	(-0.99)	(-1.26)	(-1.71)
Asset growth	-0.012**	-0.001	-0.009**	-0.011**	-0.010**	-0.001
	(-9.09)	(-0.46)	(-4.42)	(-7.67)	(-5.01)	(0.22)
IVOL		-0.007				-0.086
		(-0.10)				(-0.84)
*IVOL*Asset growth*		-0.260**				-0.48**
		(-3.87)				(-4.11)
GIBBS			0.039			-0.059
			(0.55)			(-0.92)
*GIBBS*Asset growth*			-0.217*			0.200
			(-1.97)			(1.18)
AMIHUD				0.331**		0.319**
				(2.83)		(3.23)
*AMIHUD*Asset growth*				0.446		0.291
				(1.12)		(0.89)
LOT					0.014	0.008
					(0.75)	(0.33)
*LOT*Asset growth*					-0.010	0.054
					(-0.42)	(1.11)

Table 6. Summary statistics of asset growth portfolios

Summary statistics for five equal-weighted portfolios of stocks formed at the end of June based on asset growth rate. The sample period is from 1968 through 2006. This table reports means of annual median values except for the return values which are means of portfolio returns and idiosyncratic volatility values which are pooled. Asset growth is defined as the annual change in total assets divided by the lagged value of total assets. The Hasbrouk (2006) bid-ask measure (GIBBS) is the Gibbs sampler estimate of the Roll (1984) model over the calendar year prior to the sorting year. The Amihud illiquidity measure (AMIHUD) is the Amihud (2002) measure of illiquidity calculated using stock returns and trading volume over the prior twelve months. To facilitate reporting, in this table we multiply AMIHUD by 1 million. The Lesmond, Ogden and Trzcinka (1999) measure of transaction costs (LOT) is calculated from daily stock returns over the calendar year prior to the sorting year. The annual return measures are calculated as the buy-and-hold return of the monthly raw returns for the twelve months subsequent to the June 30th sorting date. Idiosyncratic volatility (IVOL) is defined as the standard deviation of the residuals of a market model regression of firm returns over the twelve months prior and post sorting. We transform daily idiosyncratic volatility into monthly values by multiplying it by the square root of 21. ** denote significance at the 1% level, * at the 5% level.

	Asset growth rate				
	1(low)	2	3	4	5 (high)
Asset growth rate	-14.9%	0.5%	7.9%	18.3%	57.5%
Size ($ millions)	30.0	90.2	151.8	166.6	122.2
Book-to-market ratio (BM)	0.99	0.99	0.82	0.63	0.45
Mean monthly return during 12 months following sorting	1.88%	1.55%	1.35%	1.17%	0.57%
Hasbrouk measure of bid-ask spread (GIBBS)	1.5%	0.7%	0.5%	0.6%	0.7%
Amihud measure of price impact (AMIHUD)	4.2	0.8	0.3	0.3	0.4
LOT measure of transaction costs (LOT)	8.2%	4.1%	3.1%	3.2%	4.0%
Monthly idiosyncratic volatility (IVOL) 12 months pre	23.3%	15.1%	13.0%	13.7%	16.3%
Monthly idiosyncratic volatility (IVOL) 12 months post	21.7%	15.0%	13.0%	13.7%	16.5%
Difference	-1.6%**	-0.1%**	0.1%*	0.0%	0.1%**

Table 7. Portfolio returns based on two-way independent sorts

This table reports equal-weighted mean monthly portfolio returns for portfolios of stocks formed at the end of June from 1968 through 2006. Each panel presents portfolios formed based on asset growth rate defined as the annual change in total assets divided by the lagged value of total assets. Size is the market value of equity as of June 31st of the sorting year. The book-to-market ratio (BM) is defined as defined in Davis, Fama, and French (2000). Idiosyncratic volatility (IVOL) is defined as the standard deviation of the residuals of a market model regression over the twelve months prior to the sorting year. The Hasbrouk (2006) bid-ask measure (GIBBS) is the Gibbs sampler estimate of the Roll (1984) model over the calendar year prior to the sorting year. The Amihud illiquidity measure (AMIHUD) is the Amihud (2002) measure of illiquidity calculated using stock returns and trading volume over the prior twelve months. The Lesmond, Ogden and Trzcinka (1999) measure of transaction costs (LOT) is calculated from daily stock returns over the calendar year prior to the sorting year. The table presents results for two-way independent sorts based on these variables into quintiles. Portfolios are rebalanced annually. Portfolios returns are from the beginning of July of the sorting year through the end of June of the following year. We also report statistics on “high-low” and “small-large” difference portfolio returns. Over the sample period there are 468 monthly observations (12 months x 39 years of data). The t-statistics for the extreme quintile spreads are reported in brackets with ** denoting significance at the 1% level, and * at the 5% level.

Panel A. Asset growth rate and book-to-market ratio sorts

		Asset growth rate						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
	1(low)	1.2%	1.0%	0.9%	0.8%	0.2%	1.0%	[4.22**]
Book-	2	1.7%	1.3%	1.2%	1.2%	0.6%	1.0%	[5.60**]
to-market	3	1.8%	1.4%	1.3%	1.2%	0.8%	1.0%	[5.66**]
ratio	4	2.1%	1.5%	1.5%	1.3%	1.1%	1.0%	[5.60**]
	5 (high)	2.2%	2.0%	1.6%	1.5%	1.3%	0.9%	[4.85**]
	High-low	1.0%	1.0%	0.7%	0.7%	1.2%		
	[t-stat]	[4.73**]	[4.81**]	[4.18**]	[3.63**]	[4.95**]		

Panel B. Asset growth rate and size sorts

		Asset growth rate						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
	1(small)	2.03%	1.74%	1.54%	1.33%	0.65%	1.37%	[9.40]
	2	1.26%	1.33%	1.38%	1.08%	0.47%	0.79%	[5.15]
Size	3	1.29%	1.38%	1.20%	1.16%	0.58%	0.71%	[3.83]
	4	1.15%	1.23%	1.19%	1.10%	0.62%	0.53%	[2.77]
	5 (large)	1.36%	1.13%	1.07%	0.88%	0.59%	0.77%	[3.67]
	Small-large	0.67%	0.61%	0.47%	0.45%	0.07%		
	[t-stat]	2.04	2.82	2.34	2.15	0.25		

Table 7 (Continued). Portfolio returns based on two-way independent sorts

Panel C. Asset growth rate and idiosyncratic volatility sorts

		Asset growth rate						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
	1(low)	1.2%	1.3%	1.2%	1.1%	1.1%	0.1%	[1.02]
	2	1.4%	1.3%	1.3%	1.1%	0.8%	0.6%	[4.48**]
IVOL	3	1.6%	1.6%	1.5%	1.2%	0.6%	1.0%	[6.67**]
	4	1.6%	1.6%	1.4%	1.1%	0.4%	1.2%	[7.72**]
	5 (high)	2.3%	1.9%	1.6%	1.3%	0.6%	1.7%	[7.47**]

Panel D. Asset growth rate and GIBBS measure sorts

		Asset growth rate						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
	1(low)	1.4%	1.3%	1.2%	1.0%	0.7%	0.7%	[4.78**]
	2	1.2%	1.3%	1.2%	1.0%	0.6%	0.6%	[3.87**]
GIBBS	3	1.4%	1.5%	1.3%	1.1%	0.4%	1.0%	[5.72**]
	4	1.7%	1.5%	1.3%	1.2%	0.4%	1.2%	[7.24**]
	5 (high)	2.2%	1.8%	1.6%	1.4%	0.8%	1.4%	[7.10**]

Panel E. Asset growth rate and AMIHUD measure sorts

		Asset growth rate						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
	1(low)	1.3%	1.2%	1.1%	1.0%	0.4%	0.9%	[4.76**]
	2	1.1%	1.4%	1.2%	1.0%	0.4%	0.7%	[4.10**]
AMIHUD	3	1.3%	1.4%	1.2%	1.1%	0.4%	0.9%	[4.99**]
	4	1.8%	1.6%	1.5%	1.2%	0.6%	1.2%	[7.32**]
	5 (high)	2.5%	2.1%	1.8%	1.8%	1.3%	1.1%	[5.90**]

Panel F. Asset growth rate and LOT measure sorts

		Asset growth rate						
		1(low)	2	3	4	5 (high)	Low-high	[t-stat]
	1(low)	1.26%	1.22%	1.16%	0.99%	0.63%	0.63%	[3.11**]
	2	1.39%	1.37%	1.28%	1.13%	0.60%	0.79%	[4.50**]
LOT	3	1.30%	1.48%	1.38%	1.19%	0.54%	0.76%	[5.26**]
	4	1.77%	1.64%	1.35%	1.17%	0.42%	1.35%	[8.80**]
	5 (high)	2.26%	1.96%	1.82%	1.64%	1.07%	1.20%	[6.80**]

Table 8. Portfolio returns based on three-way independent sorts

This table reports equal-weighted means of monthly long-short asset growth portfolio returns for portfolios of stocks formed at the end of June from 1968 through 2006. Each panel presents portfolio returns based on three-way tercile sorts on asset growth rate, idiosyncratic volatility, and five other measures. The size terciles in Panel B are based on NYSE breakpoints. Each of the various sorting measures is defined in Table 5. Portfolios are rebalanced annually. Portfolio returns are from the beginning of July of the sorting year through the end of June of the following year. The reported values are the difference between the returns on low asset growth portfolio less the return on the high asset growth portfolio. If the median number of firms in the long or short side of the asset growth portfolio is less than 10, the value is reported as N/A. The significance of asset growth spreads are reported in brackets with ** denoting significance at the 1% level, and * at the 5% level.

Panel A. Asset growth rate, idiosyncratic volatility, and book-to-market ratio sorts

		IVOL		
		1(low)	2	3 (high)
	1(low)	0.2%*	0.5%**	1.2%**
Book-to-market ratio	2	0.2%*	0.5%**	1.2%**
	3 (high)	0.2%*	0.4%**	1.0%**

Panel B. Asset growth rate, idiosyncratic volatility, and size sorts

		IVOL		
		1(low)	2	3 (high)
	1(low)	0.2%*	0.7%**	1.3%**
Size	2	0.1%	0.6%**	1.0%**
	3 (high)	0.4%**	0.7%**	N/A

Panel C. Asset growth rate, idiosyncratic volatility, and GIBBS sorts

		IVOL		
		1(low)	2	3 (high)
	1(low)	0.3%**	0.7%**	N/A
GIBBS	2	0.3%*	0.7%**	1.2%**
	3 (high)	N/A	0.4%**	1.3%**

Panel D. Asset growth rate, idiosyncratic volatility, and AMIHUD sorts

		IVOL		
		1(low)	2	3 (high)
	1(low)	0.3%**	0.7%**	0.9%**
AMIHUD	2	0.2%*	0.6%**	1.1%**
	3 (high)	0.0%	0.5%**	1.1%**

Panel E. Asset growth rate, idiosyncratic volatility, and LOT sorts

		IVOL		
		1(low)	2	3 (high)
	1(low)	0.3%**	0.7%**	N/A
LOT	2	0.2%*	0.5%**	1.1%**
	3 (high)	0.0%	0.7%**	1.2%**

Table 9. Summary statistics of idiosyncratic volatility portfolios

Summary statistics for monthly returns of five equal-weighted portfolios of stocks formed at the end of June based on IVOL. The sample period is from 1968 through 2006. The low (high) asset growth quintile refers to the portfolio that intersects with the low (high) asset growth rate quintiles of Table 5. We present mean portfolio returns; portfolio standard deviations; and the 25th and 75th percentile of portfolio returns.

	IVOL quintiles				
	1(low)	2	3	4	5(high)
Mean (Low asset growth quintile)	1.2%	1.4%	1.6%	1.6%	2.3%
Mean (High asset growth quintile)	1.1%	0.8%	0.6%	0.4%	0.6%
Mean (Low asset growth – High asset growth)	0.1%	0.6%	1.0%	1.2%	1.7%
Std. Dev. (Low asset growth quintile)	4.1%	3.6%	3.6%	4.1%	4.5%
Std. Dev. (High asset growth quintile)	10.6%	8.8%	9.2%	9.1%	11.2%
Std. Dev. (Low asset growth – High asset growth)	2.6%	2.9%	3.2%	3.4%	4.8%
25th percentile (Low asset growth – High asset growth)	-1.4%	-1.2%	-1.0%	-1.0%	-0.4%
75th percentile (Low asset growth – High asset growth)	1.5%	2.2%	2.7%	3.0%	3.7%

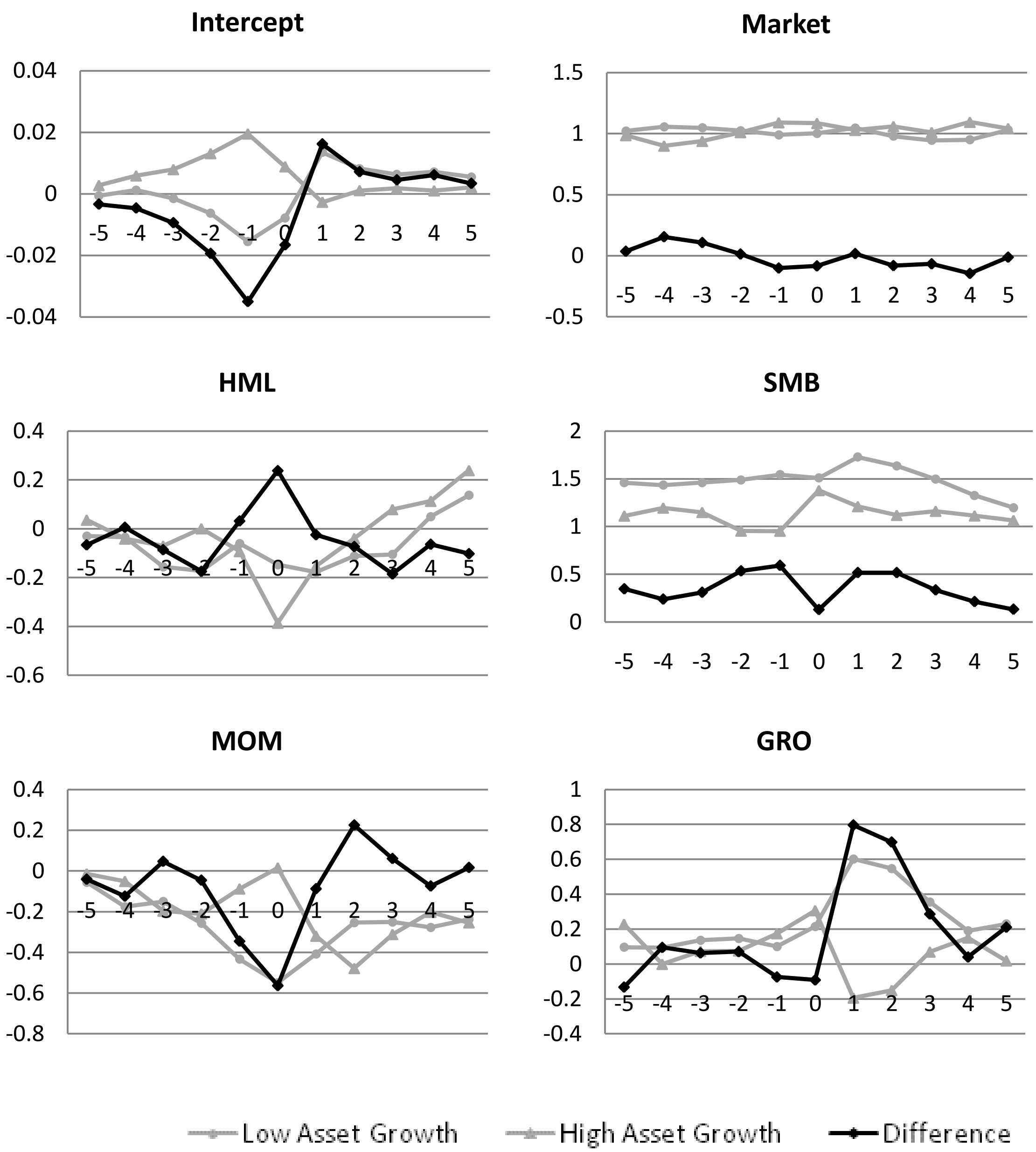

Figure 1. Asset growth portfolio return regression coefficients in event time

We sort firms at the end of each calendar year (event year 0) on asset growth quintiles, and get monthly portfolio returns for 12 months starting in July of each of the 11 years centered around the year of the sort. We run a 5 factor model on each asset growth portfolio for each event year. We plot each of the regression coefficients for the highest and lowest asset growth portfolios and for the arbitrage portfolio that takes a long position in the lowest asset growth quintile portfolio and a short position in the highest asset growth quintile portfolio.

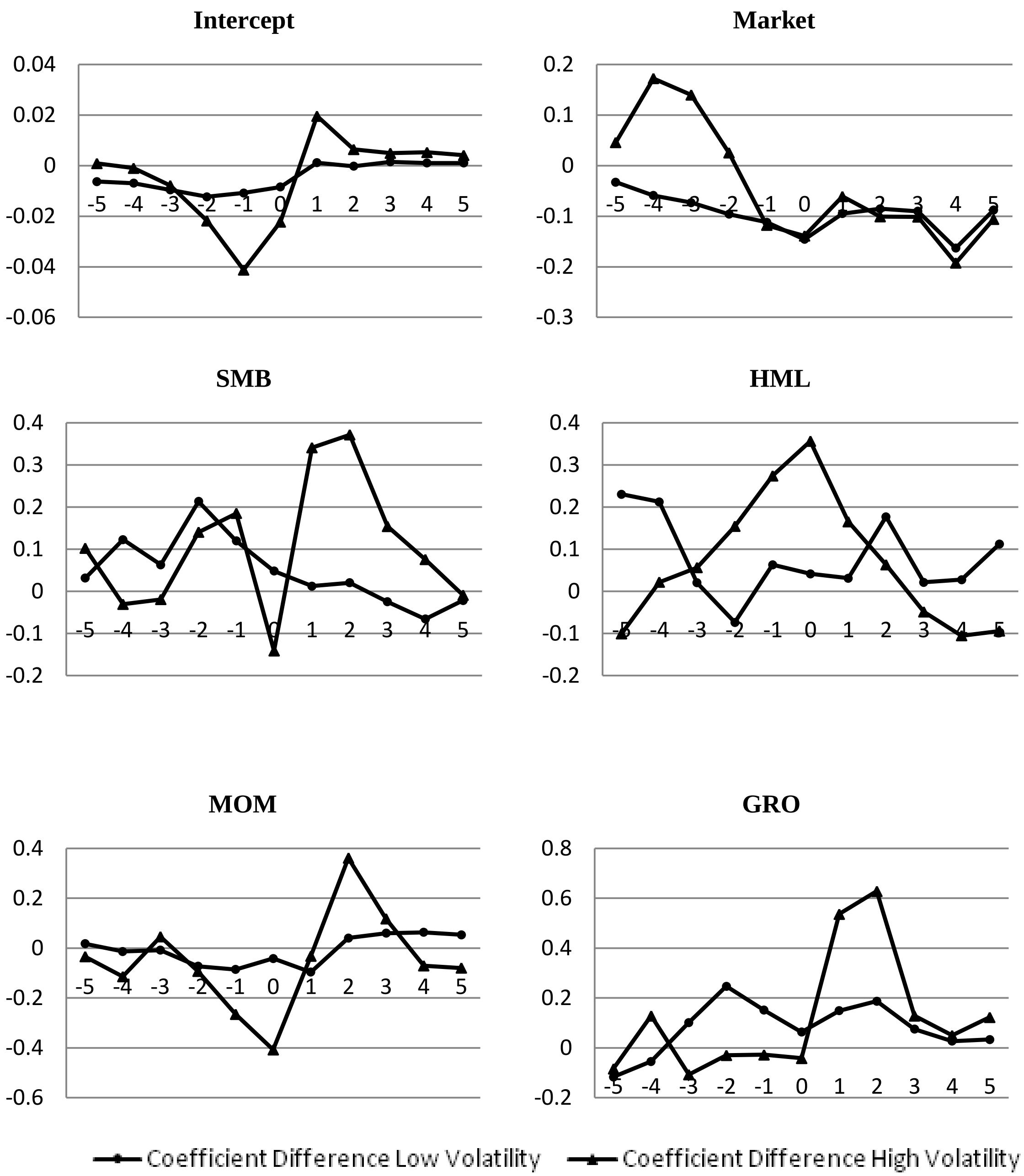

Figure 2. Asset growth return regression coefficients – volatility sorted

We sort firms at the end of each calendar year (event year 0) on asset growth and idiosyncratic volatility quintiles, and get monthly portfolio returns for 12 months starting in July of each of the 11 years centered around the year of the sort. We run a 5 factor model on each asset growth arbitrage portfolios for high and low idiosyncratic volatility stocks for each event year. We plot each of the regression coefficients for the asset growth arbitrage portfolios that take a long position in the lowest asset growth quintile portfolios and a short position in the highest asset growth quintile portfolios for low and high idiosyncratic volatility quintiles.