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On the Scope and Drivers of the Asset Growth Effect

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Abstract

Recent papers have debated whether the negative correlation between measures of firm asset growth and subsequent returns is of little importance since it applies only to small firms, is justified as compensation for risk, or is 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 other measures; 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 (IVOL); that the return effect is concentrated around earnings announcements; and that analyst forecasts are systematically higher than realized earnings for faster growing firms. In general, there appears to be no asset growth effect in firms with low IVOL. Our findings are consistent with a mispricing-based explanation for the asset growth effect in which arbitrage costs allow the effect to persist.

I. 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

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[1]Representative papers include Fairfield, Whisenant, and Yohn (2003), Titman, Wei, and Xie (2004), Broussard, Michayluk, and Neely (2005), Anderson and Garcia-Feijóo (2006), Lyandres, Sun, and Zhang (2008), Xing (2008), Cooper, Gulen, and Schill (2008), and Polk and Sapienza (2009).

offers 3 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 low asset growth are associated with relatively high 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.

Our 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, so we begin by documenting the manner in which specification choices impact inferences. Second, a number of papers have suggested that the asset growth effect arises from mispricing. This implies a relation between the asset growth effect and some limit to arbitrage. We evaluate whether the asset growth effect is linked to a common measure of arbitrage costs, idiosyncratic risk, in a set of traditional asset pricing tests including multivariate regressions and sorts. Furthermore, mispricing also implies a systematic bias in market perceptions, and we explore whether such a bias is observed in analyst forecasts. Finally, some papers suggest that the return patterns arise because asset changes are associated with changes in risk.[2] We explore 2 specific time-series predictions associated with risk explanations: There should be a change over time in risk factor loadings linked to asset growth, and the returns predicted by asset growth should not be clustered around information events. In both tests, we continue our focus on arbitrage costs and document differences related to idiosyncratic risk.

We show that the total asset growth measure of Cooper et al. (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. Alternative 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 capitalization levels.[3] 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.

[2]For example, if investment activities convert riskier growth options into less risky assets in place, then the reduction in risk justifies the lower return. Alternatively, to the extent that firms make investments when project values rise in response to future discount rate reductions (a result from the q-theory of investing), the discount rate reduction should arise from a reduction in risk and investment would therefore predict a risk reduction. Papers advancing these arguments include Tobin (1969), Yoshikawa (1980), Cochrane (1991), (1996), Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Li, Livdan, and Zhang (2009), Zhang (2005), and Xing (2008).

[3]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).

Any mispricing explanation of a persistent return pattern implicitly assumes some arbitrage cost or the pattern would be eliminated by arbitrage trading. While we explore the link between asset growth and both transaction costs (costs related to buying and selling a position) and holding costs (costs associated with maintaining a position over time), the focus of our analysis is the holding cost that arises from idiosyncratic volatility (IVOL). Holding costs are particularly relevant to our analysis, since the return patterns we study are observed over long periods of time.[4] Furthermore, transaction costs will be small in magnitude compared to the returns we are measuring, and our tests may not have the power to observe effects related to these costs. We do not make any assumption as to the particular way in which a mispricing related to asset growth would arise. The simplest explanation would be that investors respond positively to news of increased firm growth and drive prices to the upper bound allowed by arbitrage costs. As this mispricing unwinds, future returns would be attenuated. An analogous argument applies to decreasing firm growth.[5]

We observe a strong and consistent link between the asset growth effect and IVOL. In multivariate Fama-MacBeth (1973) style regressions, asset growth is shown to predict returns, but when we include the product of asset growth and IVOL, 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 a series of 3-way sorts that control for, among other things, firm size. Taken together, these results suggest that the asset growth effect is closely related to arbitrage costs. We find no evidence of a strong link between transaction costs and the asset growth effect.

If mispricing plays a role in the asset growth effect, there must exist a systematic bias in market expectations that is consistent with the specific pattern we observe. In multivariate tests similar to those exploring arbitrage costs, we explore whether such a bias is observed in analyst forecasts. Consistent with mispricing, we find that analyst forecast errors are negatively related to asset growth, and that analyst forecasts for faster growing firms are systematically higher than realized earnings.

[4]Pontiff (2006) suggests that IVOL acts as an important limit to arbitrage in that the greater the volatility of a given asset, the less weight that asset will be given in an arbitrage portfolio, thereby limiting the ability of arbitrage trading to attenuate return patterns in individual assets. One can therefore expect a link between IVOL and return patterns related to mispricing, and such links have been documented in Baker and Savaşogul (2002) (corporate mergers), Pontiff and Schill (2004) (equity offerings), and Mashruwala, Rajgopal, and Shevlin (2006) (accruals), among others.

[5]This explanation follows DeBondt and Thaler (1985) and Lakonishok, Shleifer, and Vishny (1994), who highlight mispricing arising in response to past returns or revenue, respectively. In general, investors could respond to news on changing firm operations or managers could respond to relatively high (low) market valuations by increasing (decreasing) firm investments. These explanations do not rely on a link to any particular asset investment and, in this spirit, Mortal and Schill (2009) find that the returns following firm acquisitions are no different from those following "organic" investment projects.

We also consider the possibility that the asset growth effect arises from changes in the underlying riskiness of the firm brought about by investment activities. Looking at the time series of factor loadings of an asset growth portfolio strategy (long in asset reductions and short in asset increases), we observe only modest evidence of increases in factor loadings in event time.[6] Specifically, we observe temporarily larger loadings on a subset of factors after the sorting year. However, these increases in factor loadings are observed only in portfolios constructed from high IVOL 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 is unusually negative prior to the asset growth sorting date, and unusually positive subsequently. 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.

Finally, as pointed out by La Porta, Lakonishok, Shleifer, and Vishny (1997), any risk-based explanation of a return pattern would not predict that the pattern is more pronounced during information events, whereas mispricing might be expected to unwind disproportionately when new information is released, since that information is more likely to disprove the assumptions justifying the mispricing. We find that the returns associated with the asset growth effect are disproportionately large around earnings announcements. Furthermore, confirming once again the pivotal role of arbitrage costs, the pattern is far stronger for samples of stock with high IVOL.

Our results related to arbitrage costs are consistent with explanations for asset growth based on mispricing. As such, our research is closely related to Titman et al. (2004), Cooper et al. (2008), Chan, Karceski, Lakonishok, and Sougiannis (2008), Polk and Sapienza (2009), and Li and Zhang (2010), who document an asset growth effect and provide other evidence consistent with mispricing. Of course, significant arbitrage costs must exist for any observable return pattern to be generated by mispricing (see Daniel, Hirshleifer, and Subrahmanyam (2001)). Of the papers examining mispricing, only the contemporaneous paper by Li and Zhang provides evidence of such a link, and that evidence is limited to arbitrage cost partitions of regressions otherwise focused on Q-theory explanations of asset growth effects and the link to investment limits. Our analysis provides far more extensive evidence of an arbitrage cost link by examining directly a broad set of implications from risk-based and mispricing explanations. A comprehensive consideration of the link to arbitrage costs, given its centrality to mispricing, is a needed contribution.

Our results on documenting the pervasive and dominant effect based on a single, broad measure provide a notable qualification to papers that use more narrow definitions (e.g., Fama and French (2008), Anderson and Garcia-Feijóo (2006), and Xing (2008)) and suggest that explanations acknowledging a broad effect will provide the most robust insights. To the extent that our results on the time series of factor loadings suggest that risk explanations provide only a modest

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

ability to explain the effect and that a significant mispricing pattern in alphas still exists when risk changes are accounted for, our work suggests that papers arguing in favor of an investment or asset growth risk factor may overstate the importance of such factors.[7] Clearly, our results suggest that risk cannot fully explain the observed empirical results associated with asset growth and are more readily consistent with mispricing.

The rest of the paper is organized as follows. Section II simplifies the understanding of the many manifestations of the asset growth effect. Section III provides tests of the limits to arbitrage with a focus on the role of idiosyncratic risk. Section IV examines the time-series properties of factor loadings and investigates the correlation of the asset growth effect and earnings announcement days. Section V provides concluding remarks.

II. The Asset Growth Effect

Our sample is composed of all nonfinancial firms (1-digit Standard Industrial Classification (SIC) codes not equal to 6) with data available on Compustat annual industrial files and Center for Research in Security Prices (CRSP) monthly files. To mitigate backfilling biases, a firm must be listed on Compustat for 2 years before it is included in the data set (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 statement information from the fiscal year ending by at least December 31 of the year prior to the sorting year.

A. Exploring the Variety of Asset Growth Definitions

We define 7 measures of asset growth based on past research: CGS, the total asset growth rate as defined by Cooper et al. (2008); FF, the share-adjusted asset growth rate from Fama and French (2008); LSZ, the investment-to-asset ratio from Lyandres et al. (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 3 years from Titman et al. (2004); PS, the ratio of capital expenditures to net property, plant, and equipment (PPE) from Polk and Sapienza (2009); and AGF, the firm capital expenditures divided by capital expenditures 2 years previous from Anderson and Garcia-Feijóo (2006). Each of these measures is defined in detail in the Appendix.

We construct size and book-to-market (BM) 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 BM ratio, 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 (Data 216), plus balance sheet deferred taxes and investment tax credit (Data 35), minus book value of preferred stock (in the following order: Data 56 or Data 10 or Data 130). Values for these variables are obtained for years 1968–2006.

[7]For example, Lyandres et al. (2008) and Xing (2008) make use of asset growth-based factors to explain return patterns.

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 BM ratio is 0.74, and the average median growth rates range from 5.7% to 21.5% across the different measures. The distribution of each of these measures is highly skewed. For this reason, when estimating

TABLE 1

Summary Statistics

Panel A of Table 1 reports averages of the annual median values and the average annual correlation coefficients for the various firm characteristics of U.S. stocks over the 1968–2006 period. Panel B (Panel C) reports equal-weighted (value-weighted) portfolio returns for several portfolio sorts (identified in the column headings). Portfolios are formed and re-balanced at the end of June from 1968 through 2006. The bottom row contains arbitrage portfolio returns that are long on the low quintile and short on the high quintile portfolios. The variables are: size, the market value of equity as of June 30; the book-to-market ratio (BM) as defined in Davis et al. (2000), where the market value is as 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 Data 35), minus book value of preferred stock (in the following order: Compustat Data 56 or Data 10 or Data 130) of the previous year; CGS (asset growth), the percentage change in total assets from Cooper et al. (2008); FF, the ratio of assets per split-adjusted share at the fiscal year-end divided by assets per split-adjusted share at the previous fiscal year-end following Fama and French (2008), LSZ, the investment-to-asset ratio from Lyandres et al. (2008); XING, the growth rate in capital expenditures from Xing (2008), TWX, capital expenditures divided by the average capital expenditures over the past 3 years from Titman et al. (2004); PS, the ratio of capital expenditures to net PPE from Polk and Sapienza (2009); and AGF, capital expenditures divided by capital expenditures 2 years prior from Anderson and Garcia-Feijóo (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 1 before taking the logs. The *t*-statistics for arbitrage portfolio returns (Panels B and C) are in parentheses, and ** and * indicate significance at the 1% and 5% levels, respectively.

			Asset Growth Rate Measures						
	Size	BM	CGS	FF	LSZ	PS	XING	AGF	TWX
Panel A. Summary Statistics of Firm Characteristics									
Mean	83.0	0.740	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 Feijóo (AGF)								1.000	0.884
Titman-Wei-Xie (TWX)									1.000

			Asset Growth Rate Measures						
	Size	BM	CGS	FF	LSZ	XING	TWX	PS	AGF
Panel B. Mean Equal-Weighted Returns									
1 (low)	1.3%	0.6%	1.9%	1.6%	1.7%	1.6%	1.7%	1.6%	1.6%
2	1.0%	1.1%	1.6%	1.6%	1.6%	1.4%	1.4%	1.4%	1.5%
3	1.0%	1.3%	1.4%	1.4%	1.4%	1.3%	1.4%	1.4%	1.3%
4	1.0%	1.5%	1.2%	1.2%	1.2%	1.2%	1.2%	1.2%	1.2%
5 (high)	0.9%	1.8%	0.6%	0.7%	0.7%	0.9%	0.9%	0.9%	0.9%
Low – High	0.3%	−1.2%	1.3%	0.9%	1.0%	0.7%	0.8%	0.8%	0.7%
(*t*-stat.)	(1.66)	(−6.45**)	(8.42**)	(6.08**)	(8.64**)	(7.01**)	(6.62**)	(5.08**)	(6.38**)
Panel C. Mean Value-Weighted Returns									
1 (low)	1.1%	0.7%	1.3%	1.1%	1.3%	1.1%	1.0%	1.1%	1.1%
2	1.0%	1.0%	1.1%	1.1%	1.1%	1.1%	1.1%	1.1%	1.1%
3	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%
4	1.0%	1.1%	0.9%	0.9%	0.8%	0.9%	0.9%	0.9%	0.9%
5 (high)	0.9%	1.3%	0.6%	0.7%	0.6%	0.4%	0.6%	0.6%	0.5%
Low – High	0.2%	−0.6%	0.7%	0.4%	0.7%	0.6%	0.4%	0.6%	0.6%
(*t*-stat.)	(0.83)	(−3.20**)	(4.11**)	(2.51*)	(4.80**)	(4.05**)	(2.57*)	(2.23*)	(3.66**)

correlation coefficients or performing regression analyses we winsorize the data at the 1% and 99% levels and log transform all variables. Because asset growth rate measures can take negative values, we add 1 before taking the logs. The correlation coefficient between size and the asset growth measures ranges from −0.02 to 0.16. All of the measures are negatively correlated with the BM ratio, as recognized by Anderson and Garcia-Feijóo (2006) and Xing (2008). The correlation coefficient between the BM ratio and the asset growth measures ranges from −0.12 to −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 AGF 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. The portfolios are independently created for each measure at the end of June each year based on the previous year sorting variable. In Panel B of Table 1, we provide the equal-weighted returns for portfolios formed on the basis of market capitalization, the BM ratio, and the 7 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% a month for the equal-weighted portfolios with t-statistics from 5.08 to 8.64, and from 0.4% to 0.7% for the value-weighted portfolios with t-statistics from 2.23 to 4.80.

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 returns over the past 6 months, log of size, and log of BM. We find, consistent with previous work and our portfolio results in Table 1, that size is generally negatively related to returns, and BM is positively related to returns.

We now add each of the 7 asset growth measures in turn to the right-hand side of the regression. These results are reported in Regressions 2–8. We find that all of the measures of asset growth are significantly negatively related to returns, with large t-statistics ranging from −4.71 to −9.37. The test results demonstrate the striking negative correlation between asset growth measures and subsequent returns.

Berk et al. (1999) provide a framework in which investments generate changes in risk that would lead to lower future returns. That framework also suggests that investments will explain the BM effect, and Anderson and Garcia-Feijóo (2006) test this assertion by examining whether the inclusion of a measure of asset growth (capital expenditures) reduces the BM effect. They observe a reduction in the BM effect in most (but not all) of their tests and conclude that asset growth subsumes the BM effect. When we add the asset growth variables to our baseline specification, the coefficient on BM declines somewhat from 0.003 (t-statistic = 3.85) to the lowest value of 0.002 (t-statistic = 2.99) with the CGS asset growth measure. The effect is similar for the explanatory power of size. In none of the cases does the asset growth rate measure subsume the explanatory power of the BM or size effects.[8]

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 1-year CGS measure for these specifications. These results are reported in Regressions 1–6 of Panel B of Table 2. Adding the CGS measure to the regression has a dramatic effect on the coefficients of the other asset growth measures, while adding the other asset growth measures has a modest effect on the CGS coefficient. For the FF definition, the coefficient estimate reverses sign to now be positive and significant, with the t-statistic switching from -6.39 to 3.29. The addition of the CGS total asset growth measure drives out the explanatory power of most of the other growth measures. The t-statistics drop from -7.80 to -0.80 for the LSZ measure, from -6.23 to -2.36 for the XING measure, from -6.25 to -1.16 for the TWX measure, from -4.71 to -1.22 for the PS measure, and from -6.15 to -1.60 for the AGF measure. In each of these specifications the explanatory power of the CGS measure is strong, with t-statistics ranging from -7.05 to -9.28. The coefficient on the twice-lagged value of the CGS measure is also highly significant, with t-statistics ranging from -2.27 to -3.26 in the 2 specifications that include this measure. For all but the XING measure, the alternative measures of asset growth no longer maintain any significant explanatory power. While the t-statistic for the XING measure drops from -6.23 to -2.36, the t-statistic on the CGS measures drops from -9.37 to -8.80 when both measures are included in the same regression. Later in the section, we review the residual explanatory power of the XING measure in a variety of additional tests. In the Panel B regression results, the CGS measure largely subsumes the explanatory power of the other measures.[9] The empirical relation between asset growth measures and stock returns is thus remarkably simple (the cross section of returns is strongly negatively correlated with total asset growth or the total change in the size of a firm's balance sheet).

[8]Xing (2008), like Anderson and Garcia-Feijóo (2006), hypothesizes that the BM ratio and investment variables contain similar information for future equity returns. Though in portfolio sorts she finds that the BM effect is subsumed by investment sorts, cross-sectional regressions (similar to our results) show that the BM effect is not subsumed by the inclusion of the investment variable.

[9]Cooper et al. (2008) also show that the total asset growth measure subsumes the explanatory power of various subsets of balance sheet accounts (e.g., total asset growth better explains returns than either the growth in debt or equity growth).

To further demonstrate the empirical relations across the various asset growth measures, we perform various decompositions. We begin with the Fama-French (2008) measure, which is defined as

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

and can be rearranged alternatively to

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

The alternative expression of the Fama-French measure shows that the measure is the product of 2 growth rates. The 1st term is simply the growth rate in total assets or the CGS growth measure. The 2nd term is the inverse of the growth rate

TABLE 2

Cross-Sectional Regressions of Firm Returns

Table 2 reports cross-sectional Fama-MacBeth (1973) regressions of monthly returns on various firm characteristics of U.S. stocks over the period from 1968 to 2006 (a total of 468 months). Coefficient estimates are time-series averages of cross-sectional regression coefficients, obtained from monthly regressions. The independent variables are defined in Table 1. RET6 is the 6-month return from January to June of the sorting year; CGS_{t-2} is the CGS asset growth measure lagged an extra year; PW is growth in split-adjusted shares from Pontiff and Woodgate (2008); and CGS-LSZ is LSZ subtracted from CGS. In Panel B the regressions are either equal weighted (EW) or value weighted (VW). To minimize the effect of outliers, we log transform our variables except RET6 and winsorize the data at the 1% and 99% levels except the independent variable. In parentheses are t-statistics adjusted for autocorrelation in the beta estimates, and ** and * denote significance at the 1% and 5% levels, respectively.

Panel A. All Asset Growth Rate Measures Evaluated Independently

	1	2	3	4	5	6	7	8
Intercept	0.019**	0.020**	0.019**	0.020**	0.022**	0.019**	0.020**	0.019**
	(4.15)	(4.31)	(4.15)	(4.31)	(4.95)	(4.10)	(4.20)	(4.13)
BM	0.003**	0.002**	0.003**	0.003**	0.002**	0.003**	0.003**	0.003**
	(3.85)	(2.99)	(3.54)	(3.35)	(3.30)	(3.64)	(3.46)	(3.36)
Size	−0.001*	−0.001*	−0.001*	−0.001*	−0.001**	−0.001*	−0.001*	−0.001*
	(−2.45)	(−2.16)	(−2.20)	(−2.27)	(−2.63)	(−2.28)	(−2.31)	(−2.15)
RET6	0.002	0.001	0.002	0.002	0.002	0.002	0.002	0.002
	(1.20)	(0.70)	(0.95)	(0.91)	(1.10)	(1.14)	(1.17)	(0.90)
Asset Growth Rate Measures								
CGS		−0.012**						
		(−9.37)						
FF			−0.008**					
			(−6.39)					
LSZ				−0.014**				
				(−7.80)				
PS					−0.008**			
					(−4.71)			
XING						−0.002**		
						(−6.23)		
AGF							−0.002**	
							(−6.15)	
TWX								−0.002**
								(−6.25)
R^2	0.029	0.031	0.030	0.030	0.031	0.029	0.030	0.030

(continued on next page)

TABLE 2 (continued)

Cross-Sectional Regressions of Firm Returns

Panel B. All Measures Evaluated Jointly with CGS

	EW 1	EW 2	EW 3	EW 4	EW 5	EW 6	EW 7	VW 8	EW 9	VW 10
Intercept	0.020**	0.020**	0.021**	0.020**	0.020**	0.020**	0.020**	0.014**	0.020**	0.014**
	(4.43)	(4.31)	(4.72)	(4.28)	(4.47)	(4.45)	(4.49)	(3.04)	(4.30)	(3.00)
BM	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.001	0.002**	0.001
	(3.01)	(2.97)	(3.04)	(2.97)	(2.78)	(2.70)	(2.99)	(1.42)	(2.96)	(1.19)
Size	−0.001*	−0.001*	−0.001*	−0.001*	−0.001*	−0.001*	−0.001*	−0.000	−0.001*	−0.000
	(−2.27)	(−2.16)	(−2.26)	(−2.08)	(−2.12)	(−2.02)	(−2.32)	(−0.75)	(−2.17)	(−0.74)
RET6	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.004	0.001	0.005
	(0.64)	(0.76)	(0.79)	(0.83)	(0.83)	(0.63)	(0.64)	(1.61)	(0.76)	(1.79)
CGS	−0.016**	−0.011**	−0.011**	−0.011**	−0.011**	−0.011**	−0.010**	−0.008**		−0.010**
	(−8.98)	(−7.05)	(−8.96)	(−8.80)	(−9.28)	(−9.17)	(−7.56)	(−3.54)		(−5.00)
CGS_{t-2}					−0.003*	−0.004**				
					(−2.27)	(−3.26)				
FF	0.006**									
	(3.29)									
LSZ		−0.002							−0.012**	
		(−0.80)							(−7.09)	
PS			−0.002							
			(−1.22)							
XING				−0.001*						−0.000
				(−2.36)						(−0.52)
AGF					−0.000					
					(−1.60)					
TWX						−0.000				
						(−1.16)				
PW							−0.008**	−0.011**		
							(−3.58)	(−4.06)		
CGS-LSZ									−0.010**	
									(−7.10)	
R^2	0.033	0.032	0.033	0.032	0.033	0.033	0.033	0.078	0.032	0.078

in shares outstanding. This is the measure used by Pontiff and Woodgate (2008) to show a negative correlation with subsequent returns.

By effectively multiplying the CGS measure by the inverse of the Pontiff-Woodgate (2008) measure, the Fama-French (2008) 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 2 additive terms. We alter the regression specification for the Fama-French measure by decomposing the FF measure into the 2 components: CGS and Pontiff-Woodgate (PW). This specification is reported in Regression 7 of Panel B of Table 2. The coefficients on both the CGS and PW 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 8. The coefficient estimates for both CGS and PW are significant in a value-weighted setup, with t-statistics of −3.54 and −4.06, respectively. Thus, in contrast to the conclusion in Fama and French (2008), in this test the asset growth rate maintains explanatory power for returns even among large-cap stocks.

The Lyandres et al. (LSZ) (2008) measure is identical to the CGS measure except that the numerator is based on the change in inventory and gross PPE rather than 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 the LSZ measure. We include this residual measure as a regressor with the LSZ measure in Regression 9. Due to collinearity, we do not include the CGS measure in the regression. We observe that the coefficients on LSZ and CGS-LSZ are negative, significant, and close in magnitude. The coefficient on LSZ is -0.012 (t-statistic $= -7.09$), and the coefficient on CGS-LSZ is -0.01 (t-statistic $= -7.10$). 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. The effect is not an inventory and PPE effect.

Regression 4 shows that the XING measure remains significant 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 remains significant, 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 5×5 annual sorts of stocks based on CGS and XING. These sorts are the same ones used in the quintile sorts 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 irrespective of the XING quintile. Monthly spread return levels range from 0.97% to 1.35%, with t-statistics that range from 5.44 to 6.87. For the low-high 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 total 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 most of the remaining tests in the paper.

B. Is the Asset Growth Effect Economically Material?

Fama and French (2008) claim that the asset growth effect is not economically material, as it only exists among small-cap stocks. In particular, they claim

TABLE 3

Portfolio Returns Based on Two-Way Independent Sorts

Table 3 presents equal-weighted portfolio returns based on 2-way independent sorts of XING and CGS (Panel A), Size and FF (Panel B), and Size and CGS (Panel C). Portfolio returns are from the beginning of July of the sorting year through the end of June of the following year. Following Fama and French (2008), we establish 3 size break points based on the annual 20th and 50th NYSE size percentiles. Firms below the 20% break point are denoted as "Micro." Firms between the 20% and 50% break points are denoted as "Small." Firms above the 50% break point are denoted as "Big." We sort the growth measures each year using full sample quintile break points. The *t*-statistics for the extreme quintile spreads are reported in brackets, with ** and * denoting significance at the 1% and 5% levels, respectively.

Panel A. CGS and XING Asset Growth Rate Sorts

		CGS Asset Growth Rate						
		1 (low)	2	3	4	5 (high)	Low – High	[*t*-stat.]
	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**]
XING	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.]
	Micro	1.82%	1.77%	1.61%	1.39%	0.74%	1.09%	[7.34**]
Size	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.]
	Micro	2.03%	1.74%	1.54%	1.33%	0.65%	1.37%	[9.40**]
Size	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**]

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 measures in the previous section, we construct a test that compares the Fama and French (2008) results across the 2 measures. We begin by replicating a result in the Fama and French (2008) paper by performing independent sorts by market capitalization and the FF measure. Following Fama and French (2008), we establish 3 size break points based on the annual 20th and 50th NYSE size percentiles. Firms below the 20% break point are denoted as "Micro." Firms between the 20% and 50% break points 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 (2008) in that the asset growth is smaller among large-capitalization stocks.

In Panel C of Table 3, 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 2 findings is based on the definition of the measures and in particular the dampening effect caused by the per share normalization. This normalization effectively ignores growth associated with share issuance, which we find impacts growth measures for large firms more than small firms. This suggests large firms rely on equity issuance (possibly associated with mergers) more than do smaller firms.

III. 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, Hwang, and Trombley (2003) (value effect), Lesmond, Schill, and Zhou (2004), McLean (2010) (price momentum and reversal), and Gagnon and Karolyi (2010) (cross-market effects)). 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 2 types: transaction costs and holding costs. Transaction costs are defined as those 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 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 IVOL 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 et al. (2008) estimate that the effect continues for up to 5 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.[10]

[10]In the context of our tests, the economic magnitude of any transaction cost will be much smaller than the returns we examine. Thus, while transaction costs will certainly exist for asset growth investment strategies, it is unlikely we will have the power to empirically measure these costs given the variation in returns. We include both for completeness.

A. Transaction Costs

We consider 3 transaction cost measures. We use the Gibbs sampler estimate of the Roll (1984) bid-ask spread cost measure proposed by Hasbrouck (2009). 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 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 Hasbrouck. 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 $1 of trading volume, it serves as an indicator of price impact (see Hasbrouck (2009)).

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 0 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.

B. Holding Costs and Idiosyncratic Volatility

Pontiff (1996), (2006) argues that IVOL is an important measure of holding costs in that arbitrageurs trade off the degree to which they profit from predictable return patterns against the degree of risk they incur to do so. In effect, the idiosyncratic risk exposure of the mispriced security is important to arbitrageurs because positions in that security are difficult to hedge. As a result, arbitrageurs will choose to hold lower proportions of high IVOL stocks (for a given level of mispricing), thereby slowing the adjustment speed of these stock prices to their fundamental values. A number of papers demonstrate the importance of IVOL empirically in explaining mispricing (see Baker and Savaşogul (2002) (corporate mergers), Pontiff and Schill (2004) (equity offerings), and Mashruwala et al. (2006) (accruals)).

This argument can be illustrated as follows: Consider an arbitrage portfolio of N hedge portfolios with only idiosyncratic risk exposure, each denoted by i

with IVOL equal to σ_i^2. Assuming the portfolio is correctly structured so that systematic risk has been eliminated, the resulting variance of the arbitrage portfolio can be written as

$$\sigma_p^2 = \sum_{i=1}^{N} w_i \times \sigma_i^2. \tag{3}$$

Consider the case where the expected mispricing on 2 assets, x and y, is otherwise identical, but $\sigma_x^2 > \sigma_y^2$. In this case, asset x will contribute more than asset y to the portfolio risk. A risk-averse arbitrageur creating a mean-variance optimal portfolio will choose to hold less of x and more of y.[11] Given that the extent of mispricing is inversely related to the willingness of arbitrageurs to hold a given stock, the mispricing of asset x will be greater than that of asset y.

Following past literature, we define IVOL 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 IVOL. 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.

C. Arbitrage Cost 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 4. As a reference, Regression 1 of Table 4 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 -9.37. In Regression 2 of Table 4 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 -0.244 [t-statistic $= -3.72$]. 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 -0.002 [t-statistic $= -0.62$]), suggesting that the asset growth effect exists only when in conjunction with IVOL. Furthermore, the coefficient on IVOL is insignificant,

[11]Pontiff (2006) demonstrates that the optimal portfolio weights will be equal to $w_i = \alpha_i/(\lambda\sigma_i^2)$, where λ reflects risk aversion, α_i is the alpha associated with the position in the hedge portfolio i, and σ_i^2 is the variance in returns for the hedge portfolio i.

suggesting that IVOL 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.[12]

TABLE 4

Cross-Sectional Regressions of Firm Returns with Arbitrage Cost Proxy Variables

Table 4 reports monthly Fama-MacBeth (1973) cross-sectional regressions of monthly returns on various firm characteristics over the period from 1968 to 2006 (a total of 468 months). Some of the independent variables are defined in Table 1. RET6 is the 6-month return from January to June of the sorting year. Asset growth is defined as the log change in total assets divided by the lagged total assets. Because asset growth rate can take negative values, we add 1 before taking the log. Idiosyncratic volatility (IVOL) is defined as the standard deviation of the residuals of a market model regression of firm returns over the 12 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 12 months. To facilitate reporting, in this table we multiply AMIHUD by 1,000. The Lesmond et al. (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 our variables except RET6 and IVOL and winsorize the data at the 1% and 99% levels, except the independent variable. Regressions 1–6 include the whole sample, and Regression 7 tabulates results for a sample that excludes merger firms. The nonmerger sample period is from 1982 to 2006 (a total of 300 months). Coefficient estimates are time-series averages of cross-sectional regression coefficients, obtained from monthly regressions. In parentheses are *t*-statistics adjusted for autocorrelation in the beta estimates, and ** and * denote significance at the 1% and 5% levels, respectively.

	Full	Full	Full	Full	Full	Full	No Merger
	1	2	3	4	5	6	7
Intercept	0.020**	0.019**	0.015**	0.017**	0.016**	0.018**	0.019**
	(4.31)	(6.70)	(3.31)	(3.52)	(3.74)	(6.07)	(5.13)
BM	0.002**	0.003**	0.002*	0.003**	0.002**	0.002*	0.002*
	(2.99)	(4.02)	(2.34)	(3.01)	(3.28)	(2.51)	(2.51)
Size	−0.001*	−0.001**	−0.001	−0.001	−0.001	−0.001	−0.001
	(−2.16)	(−2.78)	(−1.03)	(−0.93)	(−1.17)	(−1.76)	(−1.45)
RET6	0.001	0.001	0.002	0.000	0.000	0.002	0.000
	(0.70)	(0.33)	(0.91)	(0.21)	(0.18)	(0.95)	(0.05)
Asset Growth	−0.012**	−0.002	−0.009**	−0.011**	−0.010**	0.001	0.003
	(−9.37)	(−0.62)	(−4.45)	(−7.88)	(−5.18)	(0.35)	(0.89)
IVOL		−0.022				−0.095	0.059
		(−0.32)				(−0.95)	(0.54)
IVOL × Asset Growth		−0.244**				−0.505**	−0.453**
		(−3.72)				(−4.32)	(−3.77)
GIBBS			0.036			−0.052	−0.013
			(0.53)			(−0.85)	(−0.19)
GIBBS × Asset Growth			−0.236*			0.206	0.064
			(−2.14)			(1.20)	(0.38)
AMIHUD				0.321**		0.305**	0.159**
				(2.77)		(3.22)	(3.91)
AMIHUD × Asset Growth				0.406		0.224	0.088
				(0.97)		(0.65)	(0.57)
LOT					0.018	0.012	−0.036
					(0.95)	(0.51)	(−1.65)
LOT × Asset Growth					−0.007	0.065	0.074
					(−0.31)	(1.30)	(1.32)
R^2	0.031	0.043	0.043	0.041	0.037	0.063	0.049

In Regressions 3, 4, and 5 we consider the explanatory power of the 3 transaction cost estimates GIBBS, AMIHUD, and LOT in a similar manner to IVOL. In these regressions, we find that the AMIHUD measure is positively related to returns, which is consistent with its role as a transaction cost, but the other variables are insignificant. Thus, as expected, there is little evidence that returns measured

[12]Our results on the predictive power of IVOL differ from the work of Ang, Hodrick, Xing, and Zhang (2006) but are consistent with Bali and Cakici (2008).

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 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 4 document a link between IVOL and asset growth that is consistent with an arbitrage cost explanation.[13]

It is possible that asset growth associated with mergers differs from asset growth generated organically. In the case of mergers, for example, the motivation might be the expansion into unrelated markets rather than the accumulation of capital assets. Another possible difference is that asset growth financed with stock issuance generally arises from stock-financed mergers (see Fama and French (2005)).[14] To assess whether our central results are robust to whether asset growth is generated through acquisitions, we include as column 7 the same analysis as in column 6, but for the subsample of firms that did not execute mergers during the year prior to the sorting year. Specifically, we obtain a sample of merger firms from Securities Data Corporation (SDC) effective between 1981 and 2005, and we exclude these mergers from our total sample. Results are very similar.

As in the Table 2 regressions, the regressions in Table 4 include a BM measure, firm size, and returns in the past 6 months. As in Table 2, the BM effect continues to be significant in all our specifications, once again suggesting that the asset growth effect is independent of the BM effect. The inclusion of firm size is of particular importance in the Table 4 regressions, since it might be argued that any relation between returns and IVOL 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 IVOL interacted with asset growth exists even with size in the regressions.

D. Analyst Forecast Errors

We have argued that any persistent return pattern arising from mispricing must be accompanied by limits to arbitrage or the pattern would be eliminated. Another requirement is a systematic bias in perception that generates the specific pattern itself. While the identification of specific information or activities that drive the asset growth pattern is beyond the scope of our analysis, we do provide evidence that a systematic bias in perception exists and that the bias is consistent with the pattern we observe. In particular, to the extent that analyst forecast errors reflect market expectations and reported earnings reflect outcomes, analyst

[13]Ali et al. (2003) establish a similar relation between IVOL and the BM effect.

[14]We also explicitly test whether external financing itself is related to the asset growth effect. In regressions analogous to those in Table 4, we find that even though external financing significantly predicts future returns on its own, when asset growth is included in the regression, asset growth significantly predicts returns, and neither the external financing nor the interaction between IVOL and external financing is significant.

forecast errors would reflect the market's bias. Thus, we would expect that analyst forecasts will be biased upwards (downwards) for high (low) growth firms, leading to a negative (positive) forecast error where the error is measured as the actual earnings minus the median forecast.[15]

A critical distinction between our earlier and subsequent tests and our examination of analyst forecast errors in this section is that there is no way to arbitrage the forecast errors. Thus, in contrast to our focus on returns elsewhere, we do not propose or expect to find a relation between forecast errors and arbitrage costs.[16] Rather, the point of this analysis is that if the asset growth effect were a reflection of risk changes as a result of asset reallocations, there would be no reason for asset growth to be related to analyst forecast errors. Conversely, if the bias in forecast errors were consistent with the asset growth effect's return pattern, this would provide additional evidence that the effect is driven by mispricing.

Forecast errors have not previously been considered in the context of pricing anomalies, and we therefore have no established methodology to employ. The closest analysis of which we are aware is a paper by Scherbina (2008), which uses a regression framework to explain forecast errors and includes both BM and size as explanatory variables. To be consistent with our earlier tests and using the methodology of Scherbina, we construct Fama-MacBeth (1973) cross-sectional yearly regressions explaining analyst forecast errors using the same regressors as in our stock return tests. The analyst forecast error is defined as the difference between the actual earnings and the analyst forecast earnings for the year following the sorting year. The analyst forecast is measured as the 1st median forecast made during the period for which we measure returns. We scale forecast errors using both the stock price and the median earnings estimate.[17] When using the median earnings estimate scaling, we delete observations with nonpositive values for the scaling measure. To ensure there is some consensus in the forecasting estimates, we exclude firm-years with only a single analyst estimate. The results are presented in Table 5.

In the first 2 columns of Table 5 we observe that forecast errors are, in fact, biased in a manner that is consistent with the asset growth effect. Specifically, the forecast error is negatively related to asset growth: Faster growing firms, for example, have actual reported earnings that are lower than the analyst estimate (the analysts forecasts are biased upwards for high growth firms). Results are unchanged in the second 2 regressions, which add controls for the BM, size, and prior returns.

[15]This definition of the forecast error is most commonly used (it describes the actual results relative to the forecast). As such, it is a negative measure of the bias in the estimate, which would be more naturally defined as the forecast relative to the actual results.

[16]In unreported tests, we have verified that no such relation exists.

[17]The average annual median forecast errors are -0.0102 and -0.1162 when scaled by price and median estimate, respectively. As in previous studies, analyst errors are negative on average (the estimates are positively biased).

TABLE 5

Analysis of Analyst Forecast Errors

Table 5 reports yearly Fama-MacBeth (1973) cross-sectional regressions of analyst forecast errors on various firm characteristics. The analyst forecast error is defined as the difference between the actual earnings and the analyst forecast earnings for the year following the sorting year. The analyst forecast is measured as the 1st median forecast made during the period for which we measure returns. We scale forecast errors using both the stock price and the median earnings estimate (MEDEST). When using the median earnings estimate scaling, we delete observations with nonpositive values for the scaling measure. We exclude firm-years with only a single analyst estimate. Some of the independent variables are defined in Table 1. RET6 is the 6-month return from January to June of the sorting year. Asset growth is defined as the log change in total assets divided by the lagged total assets. Because asset growth rate can take negative values, we add 1 before taking the log. To minimize the effect of outliers, we log transform all independent variables except RET6 and winsorize all variables at the 1% and 99% levels. Coefficient estimates are time-series averages of cross-sectional regression coefficients, obtained from yearly regressions. In parentheses are *t*-statistics robust to serial correlation, and ** and * denote significance at the 1% and 5% levels, respectively.

	Scaled by Price	Scaled by MEDEST	Scaled by Price	Scaled by MEDEST
Intercept	−0.029**	−0.322**	−0.086**	−1.102**
	(−5.89)	(−6.31)	(−7.87)	(−7.24)
Asset growth	−0.016**	−0.229**	−0.018**	−0.159**
	(−3.56)	(−4.22)	(−2.92)	(−2.78)
BM			−0.005*	0.022
			(−2.13)	(1.03)
Size			0.009**	0.122**
			(8.39)	(7.15)
RET6			0.047**	0.455**
			(4.62)	(7.19)
R^2	0.004	0.007	0.067	0.063

E. Portfolio Return Tests

The cross-sectional regressions in the previous sections impose a defined structure on the relation between returns and characteristics. An alternative approach is to look at portfolios sorted on the characteristics, so that no such structure is assumed. Admittedly, our ability to control for relationships is diminished in this kind of analysis. We sort the stocks into 5 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 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 5 portfolios, we report the average annual median size and BM ratio across the groups. The low growth group tends to be fairly small ($30 million) and to have high BM ratios (0.99). The size peaks in portfolio 4 ($167 million), and the BM ratio is lowest in portfolio 5 (0.45). It is again clear that firm asset growth is correlated with the BM ratio, as suggested by Anderson and Garcia-Feijóo (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 IVOL 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 6

Summary Statistics of Asset Growth Portfolios

Table 6 presents summary statistics for 5 equal-weighted portfolios of stocks formed at the end of June based on asset growth rate. The sample period is from 1968 through 2006. The table reports means of annual median values except for the return values, which are means of portfolio returns and idiosyncratic volatility (IVOL) values that are pooled. Asset growth is defined as the annual change in total assets divided by the lagged total assets. The Hasbrouck (2009) 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 12 months. To facilitate reporting, in this table we multiply AMIHUD by 1 million. The Lesmond et al. (1999) measure of transaction costs (LOT) is calculated from daily stock returns over the calendar year prior to the sorting year. Mean monthly returns are for the 12 months subsequent to the June 30 sorting date. IVOL is defined as the standard deviation of the residuals of a market model regression of firm returns over the 12 months prior and post sorting. We transform daily IVOL into monthly values by multiplying it by the square root of 21. Here, ** and * denote significance at the 1% and 5% levels, respectively.

	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%
Hasbrouck 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 IVOL 12 months pre	23.3%	15.1%	13.0%	13.7%	16.3%
Monthly IVOL 12 months post	21.7%	15.0%	13.1%	13.7%	16.5%
Difference	−1.6%**	−0.1%**	0.1%*	0.0%	0.2%**

Table 1 reports the associated mean monthly portfolio returns for the groups over the year subsequent to the June 30 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 1.3% difference in monthly gross returns (15.6% 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 2 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 30. 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 15.6%.

Table 6 also reports the mean IVOL estimate over the prior and 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 low 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. For example, the Berk et al. (1999) model suggests that the uncertainty that is associated with growth opportunities declines after investment, as growth opportunities are transformed into less risky assets in place. If IVOL proxies for uncertainty in growth opportunities, we would expect this uncertainty to decline with investment. Our results are not consistent with this interpretation, and we explore this possibility more fully later.

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 BM, size, and asset growth effects. Assuming high investment firms are responding to the investment opportunities indicated by low BM ratios, Berk et al. (1999) suggest the BM and size effects documented in Fama and French (1992) should be explained by this asset growth effect. Anderson and Garcia-Feijóo (2006) conclude that the BM and asset growth effects are the same, and therefore the BM effect can be explained by the theoretical framework of Berk et al. (1999). 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 BM and size measures with respect to asset growth rate 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 BM 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 BM and size effects, as suggested by some risk-based models, we expect the difference in returns across BM ratio or size quintiles to disappear once these values are conditioned on the asset expansion quintile. We find that this is not the case.[18] At all levels of asset growth rate, the difference in returns is highly significant across the extreme quintiles for both the BM ratio and firm size. Thus, size and BM effects persist after sorting on asset growth, a result again inconsistent with the conclusions of Anderson and Garcia-Feijóo (2006) and Xing (2008). In Panel A of Table 7, the differences in monthly returns between the high and low BM ratio quintiles are 1.0%, 1.0%, 0.7%, 0.7%, and 1.1% across asset growth rate quintiles 1–5, respectively. There is no evidence that the BM effect disappears once firm investment policy is considered. High BM ratio stocks generate 1.1% higher monthly returns than low BM ratio stocks, even among the sample of firms that are growing assets at an average rate of 57% (see Table 6).

Most importantly, we find that the asset growth effect is also robust to controlling for size and BM levels. The difference in returns between extreme asset growth rate portfolios is almost identical across the 5 BM quintiles. We do observe a relationship with size (the asset growth effect is smaller among larger firms), as already observed by Cooper et al. (2008) and Fama and French (2008), but in both cases the difference in returns across asset growth groups is still significant among

[18]To reconcile our result with that of Xing (2008), we repeat our portfolio tests using the XING measure. In these tests we observe results similar to Xing; the BM effect is diminished with the change in capital expenditures, although the differences in quintile returns in our tests are still significant.

TABLE 7
Portfolio Returns Based on Two-Way Independent Sorts

Table 7 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 30 of the sorting year. The book-to-market ratio (BM) is as defined in Davis et al. (2000). Idiosyncratic volatility (IVOL) is defined as the standard deviation of the residuals of a market model regression over the 12 months prior to the sorting year. The Hasbrouck (2009) 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 12 months. The Lesmond et al. (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 2-way independent sorts based on asset growth and each of these variables into quintiles. Portfolios are rebalanced annually, and 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 $\times$ 39 years of data). The *t*-statistics for the extreme quintile spreads are reported in brackets, with ** and * denoting significance at the 1% and 5% levels, respectively.

		Asset Growth Rate						
		1 (low)	2	3	4	5 (high)	Low – High	[*t*-stat.]
Panel A. Asset Growth Rate and BM Ratio Sorts								
BM ratio	1 (low)	1.2%	1.0%	0.9%	0.8%	0.2%	1.0%	[4.22**]
	2	1.7%	1.3%	1.2%	1.2%	0.6%	1.1%	[5.60**]
	3	1.8%	1.4%	1.3%	1.2%	0.8%	1.0%	[5.66**]
	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%	1.1%		
	[*t*-stat.]	[4.73**]	[4.81**]	[4.18**]	[3.63**]	[4.95**]		
Panel B. Asset Growth Rate and Size Sorts								
Size	1 (small)	2.0%	1.7%	1.5%	1.3%	0.7%	1.3%	[9.40**]
	2	1.3%	1.3%	1.4%	1.1%	0.5%	0.8%	[5.15**]
	3	1.3%	1.4%	1.2%	1.2%	0.6%	0.7%	[3.83**]
	4	1.2%	1.2%	1.2%	1.1%	0.6%	0.6%	[2.77**]
	5 (large)	1.4%	1.1%	1.1%	0.9%	0.6%	0.8%	[3.67**]
	Small – Large	0.6%	0.6%	0.4%	0.4%	0.1%		
	[*t*-stat.]	[2.04*]	[2.82**]	[2.34*]	[2.15*]	[0.25]		
Panel C. Asset Growth Rate and Idiosyncratic Volatility Sorts								
IVOL	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**]
	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								
GIBBS	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**]
	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%	1.3%	[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								
AMIHUD	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**]
	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%	1.2%	[5.90**]
Panel F. Asset Growth Rate and LOT Measure Sorts								
LOT	1 (low)	1.3%	1.2%	1.2%	1.0%	0.6%	0.7%	[3.11**]
	2	1.4%	1.4%	1.3%	1.1%	0.6%	0.8%	[4.50**]
	3	1.3%	1.5%	1.4%	1.2%	0.5%	0.8%	[5.26**]
	4	1.8%	1.6%	1.4%	1.2%	0.4%	1.4%	[8.80**]
	5 (high)	2.3%	2.0%	1.8%	1.6%	1.1%	1.2%	[6.80**]

the largest quintile stocks at 0.8% [t-statistic = 3.67]. We note that these results are consistent with the cross-sectional regressions in the previous section.[19]

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 IVOL, and we shall see the same once again. We now conduct the 2-way sorts for asset growth relative to measures of arbitrage costs: IVOL (Panel C of Table 7), GIBBS (Panel D), AMIHUD (Panel E), and LOT (Panel F). We observe some increasing asset growth effect relationships across arbitrage cost quintiles that are particularly strong with IVOL. The return difference on the extreme asset growth quintiles is just 0.1% (t-statistic = 1.02) for the low IVOL stocks and increases monotonically to 1.7% per month (t-statistic = 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. Our finding corroborates the evidence in Li and Zhang (2010), who also find that the asset growth effect is strong in stocks with high IVOL and low in stocks with low IVOL.

In our previous discussion of idiosyncratic risk as a limit to arbitrage, we emphasized the arguments presented in Pontiff (2006), which demonstrates how the IVOL of an individual asset will limit a trader's willingness to hold that asset and therefore allow a mispricing pattern to persist in that asset. While this argument does not require that portfolios formed to arbitrage a return pattern retain a high degree of IVOL, for completeness we describe in Table 8 the characteristics of asset growth arbitrage portfolios created within IVOL quintiles. Specifically, we present for each IVOL quintile time-series statistics on returns for a low asset growth portfolio, a high asset growth portfolio, and a portfolio that is long the low asset growth portfolio and short the high asset growth portfolio (the arbitrage portfolio).

For each quintile of IVOL, monthly returns for the difference between the low and high asset growth portfolios range 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 2.6% per month for the lowest IVOL portfolio to 4.8% 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 Sharpe ratio comparison, as shown in the table. The values across the top 3 IVOL quintiles are flat, suggesting that an increase in return comes with a pro rata increase in IVOL. We also observe that asset growth portfolios do experience some inherent risk with the 25th and 75th percentile monthly returns gap widening with IVOL. For example, among the 2

[19]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. To accommodate additional controls, one can increase the number of sorts, but one quickly runs into problems with the size of samples in each partition. In unreported tests, we use 3-way sorts by variable terciles to control for IVOL and either the BM ratio, firm size, the GIBBS measure, the AMIHUD measure, or the LOT measure. With this setup, we still observe that the asset growth effect is increasing in the degree of IVOL.

TABLE 8

Summary Statistics of Idiosyncratic Volatility Portfolios

Table 8 presents summary statistics on the monthly returns for the low and high asset growth quintiles sorted into 5 equal-weighted portfolios based on IVOL, as described in Panel C of Table 7. The sample period is from 1968 through 2006. We present mean portfolio returns, portfolio standard deviations, and the 25th and 75th percentiles of portfolio returns.

	IVOL Quintiles				
	1 (low)	2	3	4	5 (high)
Mean (Low asset growth quintile, Panel C, column 1)	1.2%	1.4%	1.6%	1.6%	2.3%
Mean (High asset growth quintile, Panel C, column 5)	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%	5.1%	6.4%	8.0%	10.6%
Std. dev. (High asset growth quintile)	4.5%	5.9%	7.2%	8.7%	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%
Mean Low – High / Std. dev. Low – High	0.04	0.21	0.31	0.35	0.35

high IVOL stock groups, the 25th percentile return is -1.0% and -0.4%, while the 75th percentile return is 3.0% and 3.7%. Although the returns on average do get better, there is still a nontrivial probability of negative return outcomes.

IV. Time-Series Effects

As a last set of tests, we examine 2 time-series predictions associated with risk-based explanations. The 1st prediction is that risk-based explanations imply a particular change in stock risks (factor loadings) over time, and that high asset growth (for example) will be associated with a reduction in risk. A 2nd prediction is that if risks were changed, then the return patterns should not be clustered in time. In particular, the return patterns should not be clustered around information releases.

A. Time Series of Factor Loadings

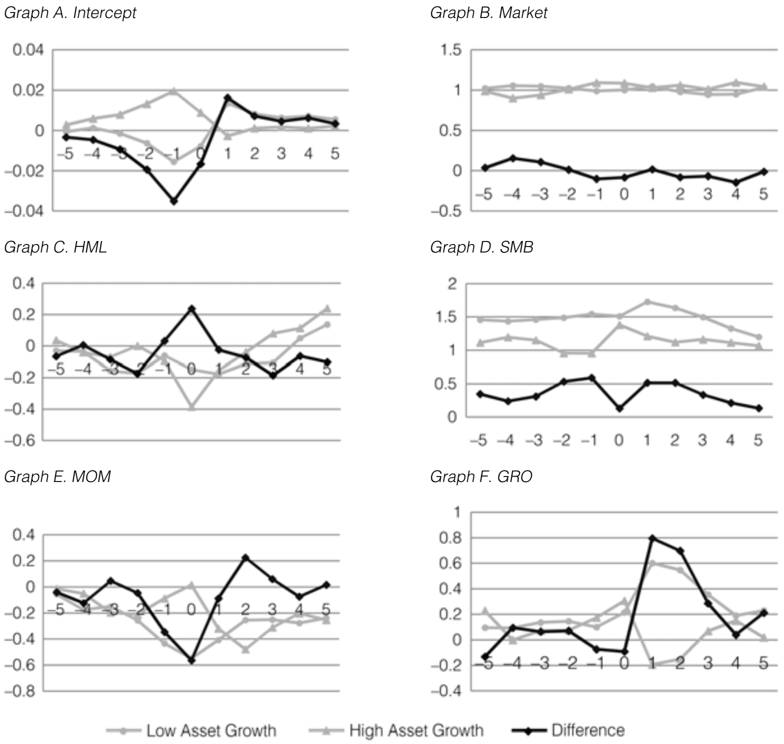
We examine the time-series characteristics of stock risks (factor loadings) and alphas over the 5 years prior to, and subsequent to, the sorting year. The goal is to evaluate how a standard asset pricing model reflects the change in risk implied by the risk-based explanations of the asset growth effect.

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. Our analysis includes standard factors and a factor related to asset growth: Market, SMB (size), HML (BM), MOM (momentum), and GRO (asset growth). We obtain the Fama and French factors from the Web site http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The asset growth factor-mimicking portfolio is constructed as follows: We first sort portfolios independently into asset growth and NYSE-size terciles as of the end of June of year t to form 9 value-weighted portfolios (our results are robust to using equal weighting). We then average the returns across the 3 size partitions for the highest and lowest factor partitions. Our zero-investment factor-mimicking portfolio is computed as the difference in returns between the extreme partitions.

FIGURE 1

Asset Growth Portfolio Returns Regression Coefficients in Event Time

In Figure 1 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.



We included a factor based on asset growth itself following several papers that have argued that the link between returns and asset growth suggests the existence of a priced factor related to investment activities. Such factor models have successfully explained some pricing anomalies (see Lyandres et al. (2008), Xing (2008)).[20] As noted in Daniel et al. (2001), the explanatory power of these factors does not preclude the possibility that they arise from mispricing, and these papers simply document that explanatory power. We do not take a position on the existence of a priced asset growth factor. However, in unreported tests following Daniel and Titman (1997), we sort firms based on asset growth and asset

[20]Lyandres et al. (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 equity issuance. Xing (2008) also shows that the asset growth effect diminishes the BM effect and attributes the result to implications of q-theory.

growth factor loadings to determine whether the factor loadings on asset growth are correlated with returns in the cross section.[21] 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. Of course, since firm characteristics can proxy for risk, the pricing power of characteristics, while consistent with mispricing, is not conclusive evidence of mispricing (see Berk (1995)).

We observe a substantial reversal pattern in the intercept of the difference portfolio consistent with Cooper et al. (2008). The magnitude of the intercept over several years after the sorting year suggests that our crude dynamic risk adjustment model with 5 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 loadings. There is some evidence that the loadings on the zero-investment portfolio increase for HML, MOM, and GRO, but these increases are fleeting.[22]

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 IVOL quintiles. In Figure 2, we plot the coefficients on the difference portfolio for each of the 2 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 IVOL.

B. Returns around Earnings Announcement Days

If the asset growth effect is associated with a change in underlying business risks, this change should affect returns equally in any subsequent time period. On the other hand, if the asset growth effect is associated with mispricing, then it is likely that mispricing would be disproportionately corrected at times when information related to firm values is released. We consider, in particular, whether the asset growth effect is disproportionately observed during the days immediately surrounding earnings announcements.

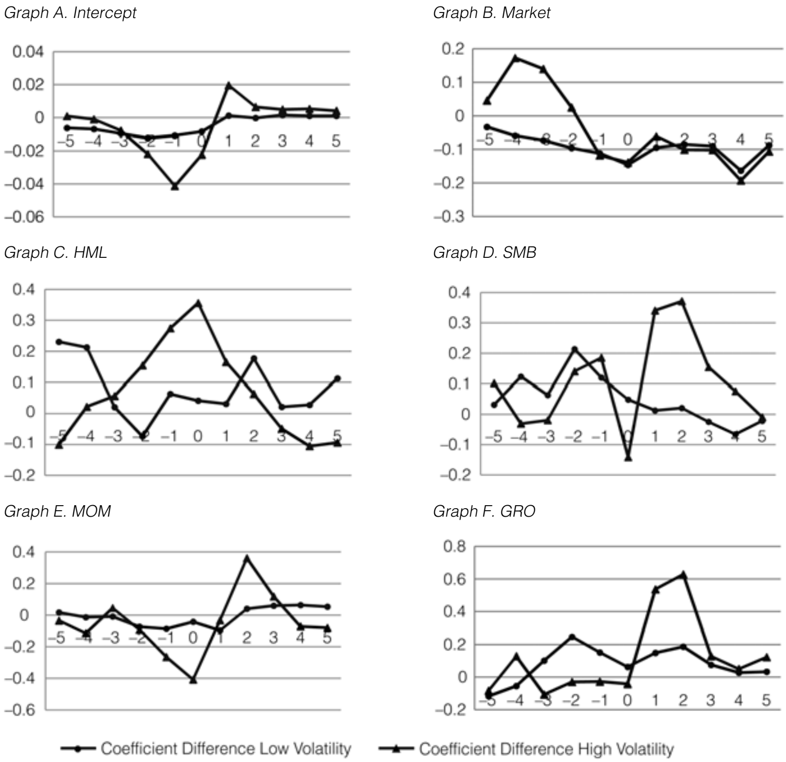
[21]The Daniel and Titman (1997) method extends the Fama and MacBeth (1973) methodology. Recent uses of this approach include the Jagannathan and Wang (1996) test of the conditional capital asset pricing model (CAPM), the Brennan, Wang, and Xia (2004) test of the intertemporal CAPM, the Campbell and Vuolteenaho (2004) test of the 2-beta model, and the Core, Guay, and Verdi (2006) analysis of an information risk factor measured by accruals.

[22]Cooper and Gubellini (2011) consider a number of return anomalies and note that the conclusions regarding whether these anomalies can be explained by risk depend greatly on specifications, and many results are not robust to differences in conditioning variables.

FIGURE 2

Asset Growth Portfolio Returns Regression Coefficients Sorted by Idiosyncratic Volatility

In Figure 2 we sort firms at the end of each calendar year (event year 0) on asset growth and idiosyncratic volatility (IVOL) 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 portfolio for high and low IVOL 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 IVOL quintiles.



We calculate the average daily return over all trading days within 1 day of an earnings announcement day (3-day windows centered on the announcement) and the average daily return over all other trading days. We then calculate the difference between these returns. The results are presented in Table 9. All results are presented after bivariate sorts based on asset growth (we present only the extreme quintiles) and IVOL. Consistent with all our other results, we observe that the difference in returns between low and high asset growth portfolios around both earnings and nonearnings announcement days is insignificant for low IVOL and becomes significant and of larger magnitude as we increase IVOL.

Important in this analysis, however, is the difference between the earnings announcement days and nonearnings announcement days. This difference is also increasing in significance with IVOL, which suggests that the magnitude of the asset growth effect is much larger on earnings announcement days. For example, for the highest IVOL quintile, the asset growth effect is 0.33% on earnings

TABLE 9

Abnormal Returns around Earnings Announcements

Table 9 reports equal-weighted returns for portfolios sorted independently on asset growth rate and idiosyncratic volatility (IVOL) quintiles. We compute average daily abnormal returns for the 3 days surrounding earnings announcements (EA), average daily abnormal returns for all other days in the quarter, and the difference in the abnormal returns surrounding EA and non-EA days. Abnormal returns are computed as the difference between the firm's daily return and the value-weighted market index for that same day. Asset growth rate is defined as the annual change in total assets divided by the lagged value of total assets. IVOL is defined as the standard deviation of the residuals of a market model regression over the 12 months prior to the sorting year. 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. We also report statistics on "low-high" difference portfolio returns. The *t*-statistics for the extreme quintile spreads are reported in brackets, with ** and * denoting significance at the 1% and 5% levels, respectively.

		EA Days			Non-EA Days			EA Days less Non-EA Days		
		Low Growth	High Growth	Low – High	Low Growth	High Growth	Low – High	Low Growth	High Growth	Low – High
	1 (low)	0.08%	0.01%	0.08%	0.01%	0.01%	0.01%	0.07%	0.00%	0.07%
				[1.86]			[1.12]			[1.71]
	2	0.14%	0.03%	0.11%	0.01%	0.00%	0.01%	0.13%	0.03%	0.09%
				[2.35*]			[1.74]			[2.12*]
IVOL	3	0.16%	−0.04%	0.20%	0.04%	0.00%	0.03%	0.12%	−0.04%	0.16%
				[3.75**]			[3.83**]			[3.25**]
	4	0.16%	−0.16%	0.31%	0.06%	0.01%	0.05%	0.10%	−0.17%	0.27%
				[6.71**]			[4.68**]			[5.72**]
	5 (high)	0.30%	−0.02%	0.33%	0.19%	0.10%	0.08%	0.12%	−0.13%	0.25%
				[4.12**]			[4.66**]			[3.32**]

announcement days and 0.08% on nonearnings announcement days. The difference, which is more than 4 times greater, is significant.

This last test provides the most direct evidence in favor of mispricing and does so along 2 dimensions. First, as we have maintained in our analysis, any mispricing explanation requires a link to arbitrage costs that would not be expected from risk-based explanations, and second, while mispricing is expected to unwind over time, we would likely observe a disproportionate unwinding at precisely those times when traders obtain new information that might lead to revisions in their assessment of value.

V. Conclusions

There are conflicting conclusions regarding the nature of the asset growth effect in stock returns, that firms with high (low) asset growth subsequently underperform (outperform) the market.[23] Some argue the effect is immaterial, some

[23]In addition to the previously mentioned papers that document the asset growth effect as a general phenomenon, a large number of papers document a similar effect 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), and Rau and Vermaelen (1998)), public equity offerings (Ibbotson (1975), Loughran and Ritter (1995)), public debt offerings (Spiess and Affleck-Graves (1999)), bank loan initiations (Billett, Flannery, and Garfinkel (2006)), and broadly defined external financing (Pontiff and Woodgate (2008), 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 et al. (2008) demonstrate that the asset growth effect is not a manifestation of these specific events, but a general phenomenon.

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 observe that the array of investment and asset growth rate measures used in the literature is effectively one effect and best captured by the total asset growth rate; that the asset growth effect seems to be limited to stocks with high IVOL; and that the time series of factor loadings and alphas provides only modest evidence of risk changes consistent with a risk explanation and, even then, limited to high IVOL stocks.

Our analysis supports 3 strong conclusions. First, the asset growth effect is economically material, pervasive across firm sizes, and linked to a broad measure of growth. Clarifying the essential nature of the effect is a valuable conclusion given the splintered nature of current research and some conflicting claims. An appreciation of the fundamental nature of the effect should focus and inform future research.

Second, we conclude that the firm IVOL is a necessary condition for asset growth effects. Evidence of this is clear in cross-sectional regressions, multivariate sorts, and the time-series patterns in factor loadings. We consider IVOL to be a strong indicator of arbitrage costs, and our results, therefore, suggest that the asset growth effect may be related to mispricing. We are not the first to suggest a link to mispricing, and Li and Zhang (2010) provide additional evidence of a link to arbitrage costs. Our contribution is a comprehensive examination of the link to arbitrage costs, including an examination of the cross section of returns (cross-sectional regressions and characteristic sorts), the times series of risk factor loadings, and the time series of returns, all considered in the context of various explanations for the asset growth effect. Given the large magnitude of returns possible from a trading strategy based on asset growth, a comprehensive examination of the link to arbitrage costs is needed. We find no evidence of a link to arbitrage costs related to trading, but those costs are likely to be small and therefore undetectable given the time spans and variability of the returns we examine.

Third, the asset growth effect is positively related to a bias in analyst earnings estimates relative to realized results. When arbitrage costs are sufficiently large, this bias is consistent with a mispricing explanation for the asset growth effect. Moreover, as would be expected if mispricing were to arise from biased expectations and those biases were corrected to a greater degree when new information is released, the asset growth effect is shown to be concentrated around earnings announcements. Our evidence suggests that market mispricing plays an important role in the asset growth effect.

Appendix. Definitions of Asset Growth Measures

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

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

FF measure: the 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 at the fiscal year-end in $t-1$ is computed as follows: (Compustat Data 6, $t-1$) / [(Compustat Data 25, $t-1$) $\times$ (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 et al. (2008), where (Data 3) is inventories, (Data 7) is gross PPE, and (Data 6) is total assets of the firm.

PS measure: (Compustat Data 128, $t-1$) / (Data 8, $t-2$) from Polk and Sapienza (2009), where (Data 128) is the capital expenditures and (Data 8) is the net PPE of the firm.

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

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

TWX measure: (Compustat Data 128, $t-1$) / Average(Data 128, $t-2$, $t-3$, $t-4$) – 1 from Titman et al. (2004), where (Data 128) 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, $t-1$) $\times$ (Compustat Data 27, $t-1$).

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