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Asset Growth and Idiosyncratic Return Volatility*

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Abstract. This paper studies the empirical relationship between firms' asset growth and idiosyncratic stock return volatility. In the cross-section, firms' idiosyncratic return volatility is V-shaped with respect to their lagged asset growth rates: the volatility is higher for firms with extreme (either high or low) asset growth rates than for firms with moderate growth rates. In the time series, a higher dispersion across firms in asset growth rates predicts a higher average idiosyncratic return volatility. Moreover, the dispersion in asset growth rates has the strongest time series predictive power among alternative explanations of the average idiosyncratic return volatility, such as cash flow volatility and growth options. These findings indicate the importance of nonlinearity in studying the cross-sectional return volatility and provide a new explanation of the idiosyncratic return volatility that is significant in both the cross-section and the time series.

JEL Classification: G12, G31

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1 Introduction

Idiosyncratic return volatility, which measures idiosyncratic risk, is important in understanding portfolio diversification, risk management, and valuation of stock options.[1] The average idiosyncratic return volatility of U.S. stocks shows an interesting movement over time. In particular, Campbell, Lettau, Malkiel, and Xu (2001) document that over the period from 1962 to 1997, there was a noticeable increase in the average idiosyncratic return volatility relative to the reasonably stable market volatility. On the other hand, Brandt, Brav, Graham, and Kumar (2010) show that the upward trend has been reversed by 2007, and the average volatility falls below pre-1990s levels. These findings have inspired extensive studies that attempt to explain idiosyncratic return volatility in both the cross-section and the time series.[2] However, the proposed explanations in the cross-section are quite different from that in the time series. More importantly, none of the existing explanations shows robust explanatory power in both cross-section and time series dimensions.

This paper fills this gap and shows that firms' asset growth rates have robust explanatory power for idiosyncratic return volatility in both dimensions. The motivation behind using asset growth to explain idiosyncratic return volatility is as follows. First, asset growth rates should contain useful information on the idiosyncratic return volatility across firms. For example, firms with a large growth in their total assets are more likely to experience large idiosyncratic uncertainties to the value of their new investment, and therefore they should have higher idiosyncratic return volatility. Similarly, firms with a negative growth are more likely to have higher uncertainties regarding the value of their existing asset-

[1] Recent empirical studies also emphasize the importance of idiosyncratic return volatility in stock returns. See, for example, Ang, Hodrick, Xing, and Zhang (2006, 2009) and Fu (2009).

[2] Existing explanations of the upward trend in the average idiosyncratic volatility include institutional ownership (Malkiel and Xu (2003), Bennett, Sias, and Starks (2003)), market composition of firms (Bennett and Sias (2006)), new listings (Brown and Kapadia (2007), Fink, Fink, Grullon, and Weston (2010)), growth options (Cao, Simin, and Zhao (2008)), product market competition (Gaspar and Massa (2006)), idiosyncratic volatility of fundamentals (Wei and Zhang (2006), Irvine and Pontiff (2009)), and financial reporting quality (Rajgopal and Venkatachalam (2011)). In addition, the cross-sectional explanations of idiosyncratic volatility include long-term earnings growth (Malkiel and Xu (2003)), idiosyncratic volatility of profitability (Pastor and Veronesi (2003)), and retail trading (Brandt, Brav, Graham, and Kumar (2010)).

s, and hence also have higher idiosyncratic return volatility. Second, the distribution of growth rates across firms should contain useful information on the cross-sectional average idiosyncratic volatility. Following the same argument as in the cross-section, if more firms have large changes in their assets (either positive or negative), more firms will have higher idiosyncratic volatility. Therefore, a higher dispersion in asset growth rates should predict a higher cross-sectional average idiosyncratic return volatility.

I first document the empirical relationship between idiosyncratic volatility and asset growth in the *cross-section*. Based on U.S. common stocks from 1963 to 2013, the idiosyncratic return volatility shows a V-shape with respect to firms' lagged annual asset growth rate. That is, stocks with extreme asset growth rates (either positive or negative) have higher idiosyncratic volatility in the following year than that of stocks with moderate growth. In addition, the V-shape is asymmetric, with a much steeper slope for firms with negative asset growth rates. The stocks with the lowest idiosyncratic volatility are associated with firms that have a moderate asset growth rate of approximately 5% per year.

I further document the robustness of the V-shaped relationship in the cross-section. First, even though stock returns affect firms' asset growth rate, the main findings still hold after controlling for the past stock returns. Second, the relationship between asset growth and idiosyncratic volatility is robust after controlling for firms' credit risk. Third, I also show that the main findings still hold using (i) alternative regression methods (e.g., pooled cross-section vs. panel regressions with fixed effect); (ii) alternative measures of volatility under different factor models; and (iii) alternative growth measures (e.g., investment-to-asset ratio).

I then compare the asset growth effect with three closely related alternative explanations of idiosyncratic volatility in the cross-section: (i) cash-flow and its volatility, (ii) growth options, and (iii) forecasted long-term earnings growth. The cross-sectional comparisons deliver two main findings. First, the asset growth effect is independent of all three explanations. The V-shaped relationship between asset growth and idiosyncratic volatility still hold even after controlling for these alternative explanations. Second, the asset growth has comparable explanatory power as cash-flow measures, but higher explanatory power than both the growth options measures and the long-term earnings growth.

Motivated by the V-shaped pattern in the cross-section, I document that in the *time series*, the cross-sectional dispersion in annual asset growth rates positively predicts the cross-sectional *average* idiosyncratic return volatility in the next year. In particular, the asset growth dispersion captures both the increase in average idiosyncratic volatility before year-2000 as documented by Campbell, Lettau, Malkiel, and Xu (2001) and subsequent sharp decline as documented by Brandt, Brav, Graham, and Kumar (2010). Moreover, the asset growth rate has a high explanatory power in the time series of the average return volatility, with a univariate R-square of 57.5%.

The positive predictive power of the asset growth measure in the time series is also robust. First, the asset growth measure is robust for an early sub-sample of time series (1963–1995), while most of other explanations luck power in the same period. Second, the predictive power of the asset growth measure is unaffected after controlling for the market-wide investor sentiment. Third, I also show that the main findings still hold using (i) alternative measures of volatility under different factor models and (ii) alternative growth measures.

I also compare the asset growth measure with alternative explanations of average idiosyncratic volatility in the time series. The main findings of the comparisons are as follows. First, the asset growth measure subsumes the explanatory power of cash-flow measures in the time series. Second, the asset growth measure provides independent and higher explanatory power than growth options measures in the full time series. In addition, for the pre-1995 time series, the asset growth measure is still significant while the growth options measures are not. Finally, I run a horse race between asset growth measure and other alternative time series explanations that have significant explanatory power. The asset growth measure is the most important predictor of the average idiosyncratic return volatility. For example, in a multiple regression with four competing measures, the asset growth measure accounts for 46% of the explained variation in the time series volatility (with the market index volatility accounts for 37% and the other two explanations account for the rest of 17%).

The contribution of this paper is threefold. First, this paper documents new empirical patterns of idiosyncratic return volatility in the cross-section. The V-shaped relationship between idiosyncratic return volatility and asset growth rate indicates the importance of nonlinearity in studying the cross-sectional return volatility. Second, this paper provides a unified explanation of return volatility in both the cross-section and time series. Finally, this paper documents a new explanation of the average idiosyncratic volatility that has the highest time series predictive power.

This paper is related to a substantial empirical literature on idiosyncratic volatility. Note that the existing explanations of idiosyncratic volatility have two notable shortcomings.[3] First, most explanations of the observed time trend in average idiosyncratic volatility before 2000 have difficulty in explaining why average idiosyncratic volatility falls during the period from 2000 to 2007.[4] Second, none of the existing explanation shows robust explanatory power in *both* time series *and* cross-section. For example, Rubin and Smith (2011) find that the market-to-book ratio, which is used by Cao, Simin, and Zhao (2008) to proxy for the growth options, is useful in the time-series context but lacks power in the cross-section. They also find that most explanatory variables in the time series have no power after controlling for the lagged volatility. In contrast, the asset growth explanation in this paper overcomes both problems. In particular, the asset growth rate can explain the up-and-then-down movement in the average volatility. Moreover, it has robust explanatory power on the idiosyncratic return volatility in both cross-section and time series.

This paper is also related to other recent empirical studies that involve asset growth and/or idiosyncratic return volatility. Cooper, Gulen, and Schill (2008) find that firms with higher annual asset growth rates will experience lower future *returns*.[5] My findings show that the asset growth is also related to the return *volatility*. Lam and Wei (2011) use the idiosyncratic return volatility as a proxy for arbitrage risks to explain the effect of asset

[3] Footnote 2 lists existing explanations of idiosyncratic volatility in both cross-section and time series.
[4] Bekaert, Hodrick, and Zhang (2012) also reject an upward trend in idiosyncratic volatility in 23 markets.
[5] Also see Titman, Wei, and Xie (2004), Anderson and Garcia-Feijóo (2006), and Xing (2008) on the relationship between investment and stock returns.

growth on returns. They find that the asset growth effect is weaker for firms with lower idiosyncratic return volatility, which they attribute to the lower arbitrage risk of these firms (also see Lipson, Mortal, and Schill (2011)). My analysis suggests that idiosyncratic return volatility in turn is also affected by the asset growth.

The paper proceeds as follows. Section 2 describes the data. Sections 3 and 4 present the empirical analysis in the cross-section and time series, respectively. Section 5 concludes the paper.

2 Data

In this section, I first describe the data sources in Section 2.1, and then show the patterns of idiosyncratic return volatility with respect to the asset growth rate through sorting and graphing in Section 2.2.

2.1 DATA SOURCES

The main analysis covers all U.S. common stocks (CRSP share-code of 10 or 11) from 1963 to 2013. Daily and monthly stock price and trading information are from CRSP and the annual accounting data are from COMPUSTAT.

The main variable of interest is the annual idiosyncratic return volatility (IVol), which is calculated from daily return residues within each month over every twelve non-overlapping months. Specifically, for every year (from July to the next June) and for each stock, I run a time series regression of daily returns on the four daily factors, that is, the three Fama-French factors plus the momentum factor. I then calculate within each month the variance of return residue from the factor regression. Finally, I average over the twelve non-overlapping months to calculate the annual frequency of idiosyncratic return volatility.[6] Note that the volatility measure is annualized, i.e., it is calculated by multiplying the daily variance by 252. In order to minimize the influence of outliers in this analysis, I winsorize the annual idiosyncratic volatility at the 99-percent level. To aggregate volatility, I use

[6] I require at least 60 daily returns within one year to prevent the factor model from over-fitting. In addition, at least 10 daily returns within one month are required to calculate the variance for each month.

value-weighting by using market capitalization as the weight. This generates a time series of annual average idiosyncratic return volatility, which is the focus of the time series analysis.

The central explanatory variable in this paper is the asset growth rate (gA), which is calculated as the annual growth rate of a firm's total book assets. In the data, there are some extreme values of asset growth rate; this mostly occurs in the case of small stocks. To deal with these extreme outliers, I winsorize the asset growth rate at the 99-percent level.

To ensure that the asset growth effect on the idiosyncratic volatility is independent of other effects, I control for a battery of variables that have been shown in the literature to be related to idiosyncratic volatility. These variables include: size, market-to-book total assets (MABA), variance of MABA (VMABA), firm age, share price, turnover, leverage, dividend dummy (DD), return on equity (ROE), and variance of ROE (VROE). Specifically, size is the market equity at the end of June. MABA is the fiscal year-end ratio of total book assets minus book equity plus market equity to total book assets. VMABA is the variance of MABA calculated using a past five-year rolling time series. Firm age is the number of years since a firm first appeared in CRSP. Share price is the nominal price per share of the stock. Turnover is the ratio of trading volume per month to outstanding shares. Leverage is the ratio of long-term debt to total assets. DD equals one for stocks that pay dividends and zero otherwise. ROE is the fiscal year-end ratio of earnings to book equity. VROE is the variance of ROE calculated using a past five-year rolling time series. Note that in regressions, I use the natural logarithms of both size and share price.

In the cross-sectional regressions, I assign accounting and price information to the explanatory variables that become available no later than the time at which the dependent variable becomes available. In particular, for regressions using average idiosyncratic volatility from July year t to June year $t+1$, I use the asset growth rate over the period $t-2$ to $t-1$, size at June t, MABA at $t-1$, VMABA calculated over the period $t-5$ to $t-1$, price at June t, average turnover during the past 12 months (July $t-1$ to June t),[7] leverage at $t-1$, DD at $t-1$, ROE at $t-1$, and VROE calculated over the period $t-5$

[7] Rubin and Smith (2011) use the concurrent turnover and find significant coefficients in both time-series and cross-sectional regressions. However, it is unclear which is the driving

to $t-1$. Thus, I use past information to explain *and predict* future return volatility. This is very similar to the procedure used by Fama and French (1992) to predict stock returns. The same timing applies to the time series analysis.

2.2 PATTERNS OF IDIOSYNCRATIC VOLATILITY

To show the relationship between idiosyncratic volatility and asset growth rate in the cross-section, I form deciles sorted by the asset growth rate for each year. For each decile and each year, I calculate the average idiosyncratic volatility and the average asset growth rate, as well as other variables of interest. I then average these variables over time, which yields time series averages of the asset growth rate, idiosyncratic volatility, and the other variables for each decile. Table 1 shows the summary statistics for the asset growth sorted deciles. Note that the raw returns of the deciles sorted by the asset growth rate are decreasing in the asset growth rate, which is consistent with the evidence documented by Cooper, Gulen, and Schill (2008).

Figure 1 plots the idiosyncratic volatility for each asset growth sorted deciles. The cross-sectional return volatility has a nice V-shape with respect to the asset growth rate. For example, the idiosyncratic volatility decreases from 0.180 at decile 1 to its lowest value 0.062 at decile 5, and then increases to 0.169 at decile 10. For the asset growth rate, it increases from -19.3% at decile 1 to 6.9% at decile 5, and then increases dramatically to 108.6% at decile 10. The volatility at deciles 1 and 10 is more than two times higher than that at decile 5. That is, the volatility decreases first and then increases as the asset growth rate increases. This offers a guidance in choosing specifications of regression in Section 3.

To visualize the relationship between idiosyncratic volatility and asset growth rate in the time series, I illustrate the time series of the average volatility and the aggregate asset growth measure from 1963 to 2013 in Figure 2. The aggregate asset growth measure (HMLgA) is the difference in average growth rates between high-growth and low-growth firms, i.e., the difference in average asset growth rates between the two segments of the V-shape (see Section 4 for more details on the construction of the aggregate asset growth

force. Intuitively, high volatility will induce high trading as well. Using past trading volume mitigates such a concern.

Table 1 Summary statistics for asset growth sorted deciles
The table reports summary statistics for portfolios sorted by asset growth rate. I first sort firms into deciles according to the annual asset growth rate (gA) for each year from 1963 to 2013. I then calculate the average asset growth and the idiosyncratic volatility within each decile for each year. Finally, I average each decile over time to calculate the time series averages. All the other variables are calculated in the same manner. Idiosyncratic volatility (IVol) is the annualized variance that is calculated from daily return residues of the four-factor return regression; Return is the monthly stock raw return; Size is the market equity measured in millions of dollars; Market assets to book assets (MABA) is the ratio of book assets minus book equity plus market equity to book assets; VMABA is the five-year rolling window variance of MABA; Age is the number of years since a firm first appears in CRSP; Price is the nominal price per share; Turn is the turnover rate calculated as the monthly trading volume divided by outstanding shares; Lev is the leverage, calculated as long-term debts divided by total assets; DD is the dividend paying dummy; ROE is the return on equity; and VROE is the five-year rolling window variance of ROE. All variables, except Size, are value-weighted.

gA decile	1	2	3	4	5	6	7	8	9	10
gA	-0.193	-0.048	0.003	0.037	0.069	0.104	0.148	0.222	0.371	1.086
IVol	0.180	0.105	0.075	0.062	0.062	0.063	0.070	0.088	0.115	0.169
Return	0.013	0.013	0.012	0.011	0.010	0.010	0.010	0.010	0.009	0.006
Size	330.3	770.5	1195	1598	1621	1840	1877	1494	1266	922.0
MABA	1.694	1.553	1.470	1.598	1.731	1.972	2.148	2.492	2.814	2.848
VMABA	1.621	0.910	0.387	0.303	0.396	0.336	0.541	0.720	1.228	2.708
Age	28.21	35.44	36.80	36.94	36.99	37.26	33.66	27.73	22.68	18.72
Price	35.79	38.04	42.82	344.0	463.9	250.5	273.6	593.0	253.5	160.9
Turn	0.096	0.085	0.073	0.064	0.066	0.066	0.072	0.087	0.109	0.134
Lev	0.224	0.209	0.202	0.198	0.186	0.168	0.166	0.160	0.182	0.215
DD	0.693	0.838	0.895	0.926	0.923	0.930	0.900	0.815	0.706	0.570
ROE	-0.106	0.063	0.108	0.133	0.139	0.154	0.161	0.167	0.159	0.119
VROE	0.216	0.056	0.031	0.021	0.016	0.011	0.019	0.024	0.037	0.126

measure). Observe that the asset growth rate dispersion between high-growth and low-growth firms matches the average idiosyncratic volatility very well, especially the rising and then falling of the average idiosyncratic volatility around year 2000. One notable outlier is the high average idiosyncratic volatility between 2008 and 2009, which involves dramatic price movements during the 2008-09 financial crisis.

3 Cross-sectional Analysis

This section provides formal cross-sectional analysis on the relationship between asset growth and idiosyncratic stock return volatility. Sections 3.1 presents the main findings,

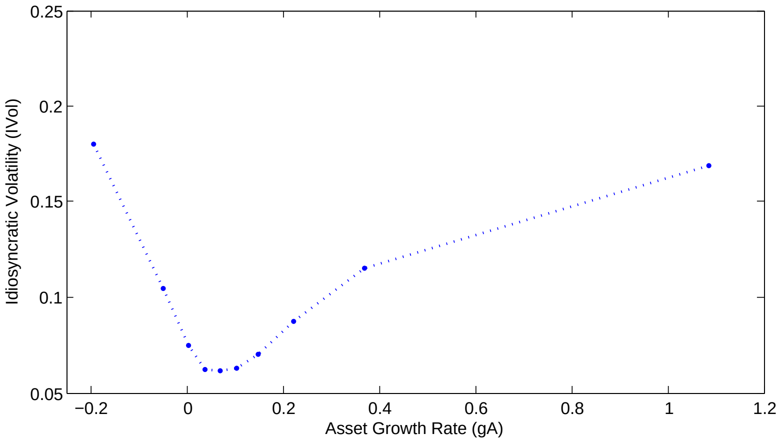

Fig. 1. Idiosyncratic volatility of asset growth deciles
The figure plots the empirical relationship between idiosyncratic return volatility and asset growth rate. I first sort firms according to their asset growth rate into deciles for each year (1963 to 2013). I then calculate the value-weighted averages of asset growth (gA) and idiosyncratic volatility (IVol) within each decile for each year. Finally, I average over time for each decile to calculate the time series averages.

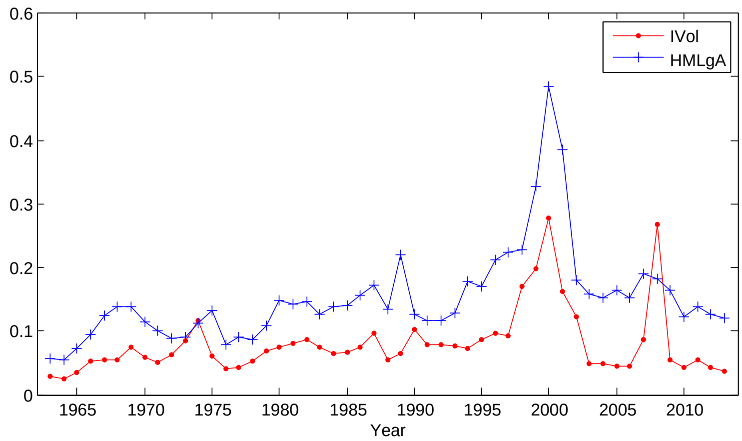

Fig. 2. Time series of average idiosyncratic volatility and asset growth
The figure plots the time series of the value-weighted average idiosyncratic volatility and the aggregate asset growth measure for the period of 1963–2013. The annual average idiosyncratic volatility (IVol) is the average of monthly volatility over 12 non-overlapping months. The monthly volatility is calculated from daily residual returns from the four-factor return regression using a 12-month non-overlapping window. The aggregate asset growth measure, denoted by HMLgA, is the difference in average asset growth rates between high-growth firms and low-growth firms, with the breaking growth rate of 5% for the two groups.

Section 3.2 shows the robustness analysis, and Section 3.3 provides further comparisons of asset growth with alternative explanations.

3.1 MAIN FINDINGS

To analyze the asset growth effect on stock return volatility, I adopt Fama and MacBeth's (1973) method for cross-sectional regressions. Specifically, for each year (which is averaged over the months from July of year t to June of year $t+1$), I run cross-sectional regressions of idiosyncratic stock return volatility (IVol_t) on the previous year's asset growth rate (gA_{t-1}). To maintain robustness, all t-statistics in the Fama-MacBeth regressions are adjusted for the first order autocorrelation of the estimates from cross-sectional regressions.

Our preliminary analysis in Section 2 (see Figure 1) reveals that the idiosyncratic volatility shows a nonlinear V-shaped relationship with asset growth. Therefore, the standard linear regression is obviously misspecified.[8] To capture the V-shaped relationship, I first estimate a piece-wise linear model with a free breaking point between low-growth and high-growth rates. The coefficient of the low-growth segment is significantly negative, and the coefficient of the high-growth segment is significantly positive, with the breaking point around 5%. This confirms the V-shape of idiosyncratic volatility with respect to the asset growth rate plotted in Figure 1.

For convenience in the multiple regressions, I transform the nonlinear regressions to linear ones. I fix the breaking point at 5% and split the asset growth rate (gA) into two variables, LgA and HgA. If the asset growth rate is *lower* than 5%, then LgA equals gA minus 5%; otherwise, LgA equals zero. If the asset growth rate is *higher* than 5%, then HgA equals gA minus 5%; otherwise, HgA equals zero. (Therefore, $\mathrm{LgA} + \mathrm{HgA} \equiv \mathrm{gA} - 5\%$.) These two variables, LgA and HgA, can capture the V-shape of volatility with respect to the asset growth rate in standard linear models without using nonlinear estimations. Specifically, the coefficient should be negative for LgA and positive for HgA.

For robustness, I also control for other variables that are related to return volatility, such as size, age and price. Note that some variables considered in the following analysis are

[8] In the simple linear regression, the coefficient of asset growth rate is insignificant, and the R-square is extremely low (0.83%).

highly correlated. For example, the correlation coefficient is 0.71 between price and size, 0.48 between price and dividend dummy, and -0.52 between ROE and VROE. Therefore, it is not appropriate to include all variables in one regression. Instead, I control for the lagged volatility as well as *one* other variable at a time. My goal here is to demonstrate the significance of the asset growth rate in cross-sectional idiosyncratic volatility, and show that the effect of asset growth on idiosyncratic volatility cannot be explained by any other control variable combined with the lagged volatility.[9]

Table 2 presents the multiple cross-sectional regressions that use the Fama-MacBeth approach. It first reports the pure asset growth effect and then controls for the lagged idiosyncratic volatility and one of the remaining variables. There are three major findings. First, the slope of the low-growth segment is about 10 times steeper than that of the high-growth segment in regression (1). This is due to the fact that firms with extreme growth rates have similar level of high volatility, but the magnitude of negative growth is much smaller than that of positive growth (see e.g. Figure 1). The slopes of both segments of the V-shape are highly significant with t-statistics of -6.05 and 11.3, which indicate that the idiosyncratic volatility is an asymmetric V-shape with respect to the asset growth rate. Second, the asset growth effect is still significant after controlling for the lagged volatility. Third, and more important, the asset growth is a significant predictor of stock return volatility in the cross-section even after the lagged volatility and other volatility related variables are controlled for. The low-growth segment has a highly significant negative coefficient, and the high-growth segment has a highly significant positive coefficient. The only exception is the seventh regression when the price is added: while HgA is still highly significant, LgA is insignificant (but still has a negative coefficient). This result is mainly driven by stocks with low per-share prices. For example, if I restrict the sample to stocks with per-share price higher than five dollars, then LgA is significantly negative and HgA is significantly positive.

The controlling variables, except for MABA, Leverage, and volatility of ROE, are significant in terms of the t-statistic at the 5-percent level. The results show that (1) volatility

[9] In the cross-sectional regression including all explanatory variables, HgA is still highly significant, while LgA is insignificant. This still shows the explanatory power of asset growth for at least high growth firms.

Table 2 Cross-sectional regressions

The table reports Fama-MacBeth regressions in the cross-section for the period from 1963 to 2013. For each year t, I run multiple regressions: $IVol_{i,t} = \alpha_t + \beta_{L,t} LgA_{i,t-1} + \beta_{H,t} HgA_{i,t-1} + \beta_{x,t} X_{i,t-1} + \epsilon_{i,t}$. The table reports the time series average coefficients ($\overline{\beta_{L,t}}$, $\overline{\beta_{H,t}}$, and $\overline{\beta_{x,t}}$) and the corresponding t-statistics. The dependent variable is the idiosyncratic volatility of firm i in year t ($IVol_{i,t}$). The two asset growth measures from year $t-1$ are: LgA equals gA - 5% for asset growth rate lower than 5%, and zero otherwise; HgA equals gA - 5% for asset growth rate higher than 5%, and zero otherwise. The other controlling variables ($X_{i,t-1}$) are: LagIVol is the lagged IVol; Size is the market equity in June of year t measured in millions of dollars; MABA is the market assets to book assets ratio for year $t-1$; VMABA is the five-year rolling window ($t-6$ to $t-1$) variance of MABA; Age is the number of years since a firm first appears in CRSP by $t-1$; Price is the nominal price per share in June of year t; Turn is the turnover rate calculated as the monthly trading volume (from July $t-1$ to June t) divided by outstanding shares in June t; Lev is the leverage at $t-1$, calculated as long-term debts divided by total assets; DD is the dividend paying dummy at $t-1$; ROE is the return on equity at $t-1$; and VROE is the five-year rolling window ($t-6$ to $t-1$) variance of ROE. Note that the natural logarithms of both Size and Price are used. The t-statistics are adjusted for the first order autocorrelation.

	LgA	HgA	LagIVol	Size	MABA	VMABA	Age	Price	Turn	Lev	DD	ROE	VROE	Adj.R^2(%)
(1)	-1.662	0.160												9.58
	(-6.05)	(11.3)												
(2)	-0.418	0.063	0.779											48.82
	(-4.38)	(5.83)	(18.4)											
(3)	-0.260	0.057	0.706	-0.056										52.52
	(-3.27)	(6.60)	(18.0)	(-3.59)										
(4)	-0.408	0.060	0.784		0.001									48.83
	(-4.18)	(5.92)	(18.3)		(0.37)									
(5)	-0.405	0.052	0.786			0.006								49.56
	(-4.10)	(7.43)	(18.4)			(4.46)								
(6)	-0.411	0.049	0.764				-0.003							49.20
	(-4.37)	(5.81)	(18.3)				(-3.10)							
(7)	-0.068	0.049	0.599					-0.158						55.42
	(-1.14)	(6.10)	(16.5)					(-3.79)						
(8)	-0.399	0.072	0.798						-0.309					50.85
	(-4.01)	(5.39)	(17.8)						(-3.44)					
(9)	-0.406	0.062	0.805							0.046				49.46
	(-4.57)	(4.40)	(17.1)							(1.97)				
(10)	-0.352	0.038	0.730								-0.127			49.90
	(-3.79)	(5.65)	(17.9)								(-3.49)			
(11)	-0.228	0.061	0.753									-0.112		49.59
	(-3.99)	(6.21)	(17.9)									(-7.63)		
(12)	-0.385	0.058	0.771										0.141	49.05
	(-4.24)	(5.81)	(18.3)										(1.75)	

is positively autocorrelated; (2) larger firms have lower volatility; (3) firms with highly volatile MABA have high volatility; (4) older firms have lower volatility; (5) higher price-per-share stocks have lower volatility; (6) dividend paying firms have lower volatility; and (7) stocks with higher return-on-equity have lower volatility.

The result in Table 2 shows that the asset growth rate is significant in explaining the idiosyncratic volatility in the multiple cross-sectional regressions. Other variables such as price-per-share and the dividend dummy also have significant effects in the cross-section. However, if these variables are valid explanations, they should be significant in the time series as well. I show later in Section 4 that only the asset growth rate is significant in both the cross-section and time series.

3.2 ROBUSTNESS ANALYSIS

In this subsection, I provide some further robustness analysis on the main findings reported above and show that the effect of asset growth on idiosyncratic volatility is robust. Specifically, I show the robustness of asset growth effect after controlling for the past return (Section 3.2.1), firms' credit risk (Section 3.2.2), and under additional robustness checks (Section 3.2.3).

3.2.1 Controlling for past stock returns

Arguably, the asset growth effect on idiosyncratic volatility can be driven by stocks with extreme past returns, i.e., past "losers" and "winners." The reasoning is as follows. Extreme return stocks tend to have extreme concurrent asset growth and high concurrent return volatility. Since the return volatility is highly persistent, stocks with extreme past returns, and hence extreme past asset growth, will have higher future return volatility. In other words, the asset growth effect documented in this paper might simply be a mechanical result of volatility persistency.

Note first that I have taken into account the persistence of idiosyncratic volatility in the multiple regression analysis in Section 3.1. Although I do find that the idiosyncratic volatility is highly persistent with a first order autocorrelation of 0.8, the asset growth measure is still highly significant when the lagged volatility is controlled for.

To further address this concern, I double sort stocks independently on the asset growth rates and past returns. Specifically, I form portfolios for July of year t to June of year $t+1$ by using returns concurrent to the asset growth measure in year $t-1$.[10] For each past return quintile, I then calculate the average idiosyncratic volatility for each asset growth decile. Although the extreme losers have much higher idiosyncratic volatility, for each past return quintile there is a V-shaped relationship between the idiosyncratic volatility and the asset growth rate similar to Figure 1. This implies that the asset growth effect on the

[10] Using returns from July $t-1$ to June t yields the same inference.

cross-sectional idiosyncratic volatility still exists even after the past returns are controlled for.

Since there is a similar V-shaped relationship between return volatility and past returns, I follow the same procedure to process the data as I did for the asset growth rate. In particular, I separate the stocks into low and high past return groups, with the breaking point of 0.9% in the monthly return. I then assign the two past return measures to each stock accordingly.

Panel (a) of Table 3 shows that although the lagged returns have explanatory power in the cross-section, the asset growth measures are still highly significant when both the lagged return and lagged volatility are controlled for. However, the effect of past winners is not robust, as the coefficient changes from positive in regression (1) to negative in regressions (2) and (3).

3.2.2 Controlling for credit risk

Avramov, Chordia, Jostova, and Philipov (2013) explore the commonalities across anomalies, focusing on the implications of financial distress. Particularly related to the current study, they find that the return effect of both the asset growth and idiosyncratic volatility in the cross-section is related to financial distress. This indicates that firms' credit conditions may be linked to both the asset growth and idiosyncratic volatility. Therefore, we need to control for the credit risk when studying the relationship between asset growth and idiosyncratic volatility.

I follow Stambaugh, Yu, and Yuan (2012) and use the Ohlson (1980) O-score as a measure of credit risk. Panel (b) of Table 3 confirms the conjecture based on prior studies that firms with higher credit risk (i.e., higher O-score) have a higher idiosyncratic volatility. However, the result also shows that the asset growth effect is still highly significant even after we control for the credit risk (with or without controlling for the lagged idiosyncratic volatility).

Table 3 Robustness analysis in the cross-section
The table reports results of the robustness analysis in the cross-section. The regression procedure is the same as that of Table 2. I run the cross-sectional regressions with the general form: $IVol_{i,t} = \alpha_t + \beta_{L,t} LgA_{i,t-1} + \beta_{H,t} HgA_{i,t-1} + \beta_{x,t} X_{i,t-1} + \epsilon_{i,t}$. The two asset growth measures from year $t-1$ are: LgA equals gA - 5% for asset growth rate lower than 5%, and zero otherwise; HgA equals gA - 5% for asset growth rate higher than 5%, and zero otherwise. The regression may include the lagged IVol (LagIVol) and other controlling variables ($X_{i,t-1}$). Panel (a) controls for the past returns. The two return measures, LReturn and HReturn, are similar to that of the two asset growth measures, except that the breaking point for past return is set at 0.9%. Panel (b) controls for the credit risk measured by O-score at $t-1$. Panel (c) compares the asset growth with cash-flow measures. ROE is the return on equity at $t-1$ and VROE is the five-year rolling window ($t-6$ to $t-1$) variance of ROE. Panel (d) compares the asset growth with growth options. MABA is the market assets to book assets ratio for year $t-1$ and VMABA is the five-year rolling window ($t-6$ to $t-1$) variance of MABA. Panel (e) compares the asset growth with long-term earnings growth. EPSLTG is the long-term growth in earnings-per-share obtained from IBES. Panels (a-d) use data from 1963–2013, and panel (e) uses data from 1982–2013.

		LgA	HgA	LagIVol	LReturn	HReturn	Adj. R^2(%)
(a) Past returns	(1)				-6.894	2.036	12.96
					(-5.21)	(10.9)	
	(2)			0.812	-1.865	-0.088	50.79
				(19.2)	(-4.06)	(-0.53)	
	(3)	-0.278	0.062	0.794	-1.632	-0.306	51.30
		(-4.55)	(6.42)	(18.9)	(-3.95)	(-2.13)	
			LagIVol	LgA	HgA	O-score	Adj. R^2 (%)
(b) Credit risk	(4)					0.033	7.48
						(7.40)	
	(5)			-1.252	0.129	0.027	13.47
				(-7.42)	(10.71)	(5.56)	
	(6)		0.743	-0.293	0.056	0.012	48.54
			(17.51)	(-4.39)	(6.11)	(4.50)	
		LagIVol	LgA	HgA	ROE	VROE	Adj. R^2(%)
(c) Cash flows	(7)				-0.399	0.556	11.30
					(-9.39)	(1.12)	
	(8)		-1.040	0.148	-0.338	0.548	15.83
			(-5.09)	(10.3)	(-8.69)	(0.86)	
	(9)	0.750	-0.216	0.061	-0.122	0.131	49.73
		(18.0)	(-3.79)	(6.34)	(-7.69)	(0.92)	
		LagIVol	LgA	HgA	MABA	VMABA	Adj. R^2(%)
(d) Growth options	(10)				-0.016	0.037	3.53
					(-1.75)	(6.08)	
	(11)		-1.606	0.134	-0.018	0.030	11.91
			(-5.62)	(9.07)	(-2.14)	(5.83)	
	(12)	0.785	-0.405	0.052	-0.004	0.007	49.68
		(18.3)	(-4.03)	(7.02)	(-1.10)	(5.05)	
			LagIVol	LgA	HgA	EPSLTG	Adj. R^2 (%)
(e) Long-term earnings growth	(13)					0.967	7.46
						(3.04)	
	(14)			-1.005	0.050	0.896	11.37
				(-5.77)	(3.92)	(3.04)	
	(15)		1.073	-0.163	0.022	0.014	40.13
			(10.1)	(-3.38)	(3.24)	(0.17)	

3.2.3 Additional robustness checks

I further consider three types of robustness checks. To save space, I report only the findings without tabulating the results.

First, I consider alternative regression methods to the Fama-MacBeth regressions. Specifically, I consider both pooled cross-section regressions and panel regressions with fixed effects (both fixed firm and fixed year effects), where the standard errors in both cases are calculated by double clustering by firm and year.[11] Under these alternative cross-sectional regression methods, the V-shaped relation between idiosyncratic volatility and asset growth still holds.

Second, I repeat the analysis by using different time frequency of the volatility measure. Specifically, I show that the main findings reported in Sections 3.1 still hold when monthly frequency of volatility is used.

Finally, I consider alternative measures of both the volatility and the asset growth measures. For the volatility, I consider four different measures: (i) Fama-French three-factor model adjusted IVol, (ii) the CAPM adjusted IVol; and (iii) the market return adjusted IVol (that is, the volatility of stock return in assess of market return), and finally (iv) total volatility, which is model-free. For growth rate, I consider two alternative measures: (i) the contemporaneous asset growth rate instead of the lagged growth rate and (ii) the lagged investment-to-assets ratio as an alternative to the asset growth rate. The main findings reported in Section 3.1 still hold.

3.3 COMPARISONS WITH ALTERNATIVE CROSS-SECTIONAL EXPLANATIONS

Next, I compare the asset growth effect in the cross-section with three closely related alternative explanations: cash flows (Section 3.3.1), growth options (Section 3.3.2), and long-term earnings growth (Section 3.3.3). The purpose of the comparison is to show that the asset growth effect is independent of these alternatives and in most cases more robust than these alternatives.

[11] See Petersen (2009) for a comprehensive study that compares different approaches to panel data regressions in the finance literature. See Cameron, Gelbach, and Miller (2011) and Thompson (2011) for clustered standard errors in multiple dimensions.

3.3.1 Asset growth versus cash flows

Pastor and Veronesi (2003) examine the idiosyncratic risk in a valuation model where investors learn about profitability. They define profitability as the cash flow per dollar book value of equity. They find that younger stocks, stocks that pay no dividends, and high market-to-book equity stocks have more volatile returns. Wei and Zhang (2006) use return-on-equity (ROE) and its time series variance (VROE) as the proxies of profitability and its uncertainty.

Here I follow Wei and Zhang (2006)'s measures of cash flow (i.e., ROE) and volatility of cash flow (i.e., VROE). The cross-sectional comparisons between asset growth and cash-flow variables are reported in panel (c) of Table 3. Lower ROE firms have higher IVol, but VROE is insignificant. The V-shaped relationship between IVol and asset growth rate is still highly significant after controlling for either ROE and VROE or in addition the lagged volatility.

I conclude that the asset growth effect is independent of the cash-flow effect. As I report in the Section 4, the cash-flow measures do not have explanatory power in the time series comparisons.

3.3.2 Asset growth versus growth options

Cao, Simin, and Zhao (2008) argue that firms with more growth options, proxied by the market-to-book assets ratio (MABA), or with higher variations in growth options, proxied by the time series variance of MABA (VMABA), should have higher idiosyncratic volatility. However, they only test their explanation in a time series without showing cross-sectional evidences. I conduct such a cross-sectional test with measures in Cao, Simin, and Zhao (2008) and do not find strong support of their explanation. As shown in panel (d) of Table 3, MABA is insignificant while VMABA is highly significant in the cross-sectional regression. However, the R-square explained by MABA and VMABA is very low (3.53%). Note that the asset growth measures are still significant in the cross-sectional regressions after both MABA and VMABA are controlled for.[12]

[12] It is worthwhile to point out that there also exists a V-shaped relationship between the idiosyncratic volatility and the market-to-book assets ratio. However, the number of

The above results show that the two measures used by Cao, Simin, and Zhao (2008) (MABA and VMABA) in the time series lack explanatory power in the cross-section. In contrast, after both measures are controlled for, the asset growth maintains its explanatory power in the cross-section. This indicates that the asset growth measure is a better explanation for cross-sectional idiosyncratic volatility than MABA, the proxy of growth options.

3.3.3 Asset growth versus long-term earnings growth

In this section, I distinguish between the asset growth measure and the expected long-term growth, which Malkiel and Xu (2003) proxy with the expected growth of long-term earnings, i.e., the earnings per share (EPS) growth as forecasted by IBES over the next 3 to 5 years. Although both the asset growth rate and EPS growth are growth measures, they have obvious differences. First, the asset growth rate measures the total asset growth, while the EPS growth is the growth of earnings *per share*. So if a firm grows by issuing new shares without changing its EPS, the asset growth measure still captures this growth while EPS does not. Second, the asset growth is the realized past asset growth, while EPS growth is the forecasted future growth. Compared to the realized asset growth rate, the forecasted EPS growth can have substantial noises. Third, the asset growth measure is available for almost all public firms since 1963, while EPS long-term growth is only available from early 1980s and for relatively large stocks.

Nevertheless, I still separate the two types of growth in the cross-sections where both measures are available. I collect long-term EPS growth from IBES for the period from 1982 to 2013. I use the median of monthly forecasts to calculate the annual average of the forecasted EPS long-term growth. I then match the long-term growth rate calculated from July of year $t-1$ to June of year t based on IBES forecasts with the average monthly

firms in the two segments of the V-shape is quite different. In the case of the asset growth rate, the two segments of the V-shape have almost the same number of stocks, with the breaking point in decile 5 (see Table 1). However, in the case of MABA, the left segment has much fewer stocks and the breaking point is in decile 3. Moreover, taking into account the nonlinearity, the MABA effect on the idiosyncratic volatility only delivers a relatively low R-square of 3.11%. Recall from Table 2 that the pure asset growth effect has an R-square of 9.58%.

volatility from July of year t to June of year $t+1$. The pooled cross-sectional correlation between the asset growth rate and long-term EPS growth is only 0.37, indicating that the two are not highly correlated.[13]

Panel (e) of Table 3 reports results with the long-term earnings growth. First, the long-term earnings growth is not significant once lagged volatility is added to regression (15). Note, however, that the asset growth is highly significant in this smaller sample in regressions (14) and (15). More important, the asset growth effect has the same asymmetric V-shape as in the main analysis. This shows that the past realized asset growth has explanatory power for idiosyncratic volatility in additional to the forecasted long-term earnings growth.[14]

4 Time-series Analysis

This section provides formal time series analysis on the relationship between asset growth and idiosyncratic stock return volatility. Section 4.1 presents the main findings. Sections 4.2 and 4.3 provide robustness analysis and compare asset growth with alternative time series explanations.

4.1 MAIN FINDINGS

To assess the time series effect of the asset growth rate on return volatility, I form time series based on both the aggregate asset growth measure and the aggregate idiosyncratic volatility. Inspired by the cross-sectional result that the volatility has a V-shaped relationship in the asset growth rate, I adopt the dispersion of the cross-sectional asset growth

[13] Note that the idiosyncratic volatility in Malkiel and Xu (2003) is calculated using returns in three years (one year before and two years after the IBES statistic period). My idiosyncratic volatility measure is calculated using returns of 12 months after the asset growth rate is known.

[14] It is worth noting that Malkiel and Xu (2003) also find an asymmetric V-shaped relationship between the idiosyncratic volatility and long-term earnings growth. However, I find that introducing the V-shape generates a very small gain in R-square relative to a simple linear model. This contrasts with my results, which show that both the low-growth and high-growth segments are very important in the cross-sectional idiosyncratic volatility regressions.

rate between high-growth and low-growth firms as the annual aggregate asset growth measure. The dispersion, denoted by HMLgA, is calculated as the average of HgA minus the average of LgA.[15]

As in the cross-sectional analysis, I also control for other variables that are related to return volatility in the time series. I construct the other aggregate variables in a similar manner as I did for the aggregate volatility. For example, the aggregate market-to-book assets measure is calculated as the cross-sectional value-weighted average of market-to-book assets. Data show that the correlations among these explanatory variables in the time series are very high. For example, the correlation coefficient is 0.90 between size and VROE, 0.87 between size and turnover, and -0.97 between size and dividend dummy. Given such high correlations among these time series, it is not appropriate to control for several variables at the same time due to potential multicollinearity. This is especially true for relatively short time series, as I have only 51 time series observations. Therefore, as I did in the cross-sectional analysis, I only control for the lagged volatility and one of the other variables when assessing the explanatory power of the asset growth measure. My goal here is to demonstrate the significance of the asset growth rate in the time series and show that the effect of asset growth on idiosyncratic volatility cannot be explained by any other control variable combined with the lagged volatility.[16]

To assess the level of residual autocorrelations, I calculate the Durbin-Watson (DW) statistic in all time series regressions. The deviation of the Durbin-Watson statistic from 2 shows the autocorrelation of regression residues. Specifically, DW smaller than 2 shows positive autocorrelation, while DW larger than 2 shows negative autocorrelation. Note that the t-statistics for all annual time series regressions are adjusted for the residual autocorrelation through Newey-West adjusted standard errors with a lag length of 2.

Table 4 reports results for multiple time series regressions. There are four important results. First, the aggregate asset growth measure is significantly positive in the time series (with a t-statistic of 10.4) and it explains 57.5% of the variations in the average

[15] An alternative to the HMLgA measure is the cross-sectional standard deviation of asset growth rate, which gives the same inferences in the time series regressions. These two measures have a correlation of 0.97.

[16] Even in the full regression including all the control variables, the asset growth measure is still highly significant in the time series.

Table 4 Time series regressions
The table reports results of the time series regressions using value-weighted data from 1963 to 2013. The regressions have the following general form: $\overline{IVol_t} = \alpha + \beta_{gA} HMLgA_{t-1} + \beta_x X_{t-1} + \epsilon_t$. The dependent variable is the average idiosyncratic volatility ($\overline{IVol}$), which is calculated as the cross-sectional average idiosyncratic volatility for each year. The aggregate asset growth measure, denoted by HMLgA, is the difference in average asset growth rates between high-growth firms and low-growth firms, with the breaking annual asset growth rate of 5%. The other controlling variables (X_{t-1}) are: LagIVol is the lagged average IVol; Size is the average market equity in June of year t measured in millions of dollars; MABA is the average ratio of market assets to book assets for year $t-1$; VMABA is the average five-year rolling window ($t-6$ to $t-1$) variance of MABA; Age is the average number of years since a firm first appears in CRSP by $t-1$; Price is the average nominal price per share in June of year t; Turn is the average turnover rate calculated as the monthly trading volume (from July $t-1$ to June t) divided by outstanding shares in June t; Lev is the average leverage at $t-1$, calculated as long-term debts divided by total assets; DD is the average dividend paying dummy at $t-1$; ROE is the average return on equity at $t-1$; and VROE is the average five-year rolling window ($t-6$ to $t-1$) variance of ROE. DW is the Durbin Watson statistic. The t-statistics are calculated using Newey-West adjusted standard errors with a lag length of 2.

	HMLgA	LagIVol	Size	MABA	VMABA	Age	Price	Turn	Lev	DD	ROE	VROE	DW	R^2(%)
(1)	0.525												2.01	57.50
	(10.4)													
(2)	0.518	0.014											2.03	56.63
	(5.52)	(0.11)												
(3)	0.545	0.016	-0.003										2.08	56.06
	(6.57)	(0.13)	(-0.53)											
(4)	0.425	0.018		0.013									1.95	57.39
	(4.52)	(0.15)		(1.92)										
(5)	0.572	0.046			-0.006								2.16	56.93
	(5.02)	(0.33)			(-1.89)									
(6)	0.518	0.021				-0.001							2.06	55.96
	(5.76)	(0.16)				(-0.45)								
(7)	0.505	0.037					0.013						2.04	55.93
	(5.46)	(0.27)					(0.72)							
(8)	0.522	0.032						-0.035					2.06	55.90
	(6.25)	(0.20)						(-0.27)						
(9)	0.497	0.008							-0.335				2.03	56.03
	(5.10)	(0.06)							(-0.57)					
(10)	0.558	0.023								0.052			2.10	56.22
	(6.42)	(0.18)								(0.66)				
(11)	0.511	0.017									0.104		2.05	55.82
	(5.53)	(0.13)									(0.29)			
(12)	0.651	0.016										-0.382	2.21	59.75
	(5.68)	(0.14)										(-2.96)		

idiosyncratic volatility. Second, the lagged volatility is not significant once the asset growth is controlled for. This shows the superior explanatory power of the asset growth even compared to the lagged volatility.[17] Third, all the other competing variables except MABA

[17] Rubin and Smith (2011) demonstrate in a simulation that inferences in regressions with both highly persistent dependent variable (e.g., the time series of average volatility) and independent variables (e.g., average price or average market-to-book ratio) suffer from a spurious regression problem, as discussed in Ferson, Sarkissian, and Simin (2003). They also find that the Newey and West (1987) approach is inadequate to correct such a

and VROE are not significant once the lagged volatility is added to the regression. Lastly, even though MABA is still significant in the multiple regression, it does not improve the adjusted R-square after the asset growth measure is included. Note also that even though VROE is significant in the multiple regression, it changed sign from positive in an univariate to negative in the multiple regression. Overall, the evidence in Table 4 shows that the aggregate asset growth is the most significant explanatory variable for the aggregate idiosyncratic volatility in the time series.

Combining the results from the cross-section (Table 2) and time series (Table 4), we can conclude that the asset growth measure has significant explanatory power in both the cross-section and the time series. MABA is the only other variable which is also significant in the both the univariate and multiple time series regressions. However, MABA lacks power in the cross-section. Even in the time series, the asset growth effect is more important than MABA in terms of R-square in explaining the average idiosyncratic volatility. This implies that the asset growth measure is the *only* explanation that is significant in both cross-section and time series.

4.2 ROBUSTNESS ANALYSIS

In this subsection, I provide some further robustness analysis on the main findings reported above and show that the effect of the asset growth on idiosyncratic volatility is robust. Specifically, I show the robustness of asset growth effect for an early subsample of time series (Section 4.2.1), controlling for market sentiment (Section 4.2.2), and under additional robustness checks (Section 4.2.3).

4.2.1 An early sub-sample of time series

Rubin and Smith (2011) find that the existing explanations of the average idiosyncratic volatility lack power in the pre-1995 period, which excludes the episode of rising and then falling idiosyncratic volatility around year 2000. Here I conduct time series regressions and show that the asset growth has a robust explanatory power for the pre-1995 sub-sample.

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problem. Instead, simply controlling for the lagged dependent variable (i.e., the average volatility) gives correct inferences without eroding the power of the tests.

Table 5 Robustness analysis in the time series

The table reports results for the robustness analysis in the time series. The time series regressions are conducted similar to those in Table 4. The regressions have the following general form: $\overline{IVol_t} = \alpha + \beta_{gA} HMLgA_{t-1} + \beta_x X_{t-1} + \epsilon_t$. The dependent variable is the average idiosyncratic volatility ($\overline{IVol}$), which is calculated as the cross-sectional average idiosyncratic volatility for each year. The aggregate asset growth measure, denoted by HMLgA, is the difference in average asset growth rates between high-growth firms and low-growth firms, with the breaking annual asset growth rate of 5%. The regression may include the lagged average volatility (LagIVol) and other controlling variables (X_{t-1}). Panel (a) uses data from 1963 to 1995 with 33 observations and the growth options measure MABA is the average ratio of market assets to book assets. Panel (b) controls for investor sentiment using data from 1965-2010; Panel (c) compares the asset growth with cash-flow measures using data from 1963–2013. ROE is the average return on equity at $t-1$; and VROE is the average five-year rolling window ($t-6$ to $t-1$) variance of ROE. Panel (d) compares the asset growth with growth options using data from 1963–2013. VMABA is the average five-year rolling window ($t-6$ to $t-1$) variance of MABA. DW is the Durbin Watson statistic. The t-statistics are calculated using Newey-West adjusted standard errors with a lag length of 2.

			LagIVol	HMLgA	MABA	DW	Adj. R^2(%)
(a) Pre-1995 time series	(1)				-0.005	0.91	-2.03
					(-0.50)		
	(2)			0.315		1.44	28.31
				(2.72)			
	(3)			0.327	0.003	1.43	26.37
				(2.86)	(0.38)		
	(4)		0.439	0.215	0.007	1.96	40.23
			(3.14)	(2.80)	(0.89)		
			LagIVol	HMLgA	Sentiment	DW	Adj. R^2(%)
(b) Sentiment	(5)				0.012	1.07	3.44
					(1.83)		
	(6)			0.514	-0.000	2.06	53.28
				(9.38)	(-0.18)		
	(7)		-0.003	0.516	-0.000	2.06	52.17
			(-0.02)	(5.44)	(-0.17)		
		LagIVol	HMLgA	ROE	VROE	DW	Adj. R^2(%)
(c) Cash flows	(8)			0.268	0.521	1.12	13.45
				(0.48)	(1.31)		
	(9)		0.658	0.252	-0.417	2.25	60.37
			(8.64)	(0.64)	(-2.45)		
	(10)	0.023	0.648	0.256	-0.418	2.29	59.54
		(0.19)	(5.51)	(0.65)	(-2.47)		
		LagIVol	HMLgA	MABA	VMABA	DW	Adj. R^2(%)
(d) Growth options	(11)			0.047	0.000	1.13	38.59
				(2.90)	(0.04)		
	(12)		0.497	0.021	-0.010	2.01	60.16
			(6.50)	(2.47)	(-3.08)		
	(13)	0.074	0.465	0.021	-0.010	2.13	59.59
		(0.56)	(4.48)	(2.60)	(-3.91)		

As shown in Section 4.1, the growth options measure, MABA, is the only variable that is significant in the time series regression in addition to the asset growth measure and the lagged volatility. Panel (a) of Table 5 reports the time series regression result including both the asset growth and the growth options measure. First, the asset growth measure is still highly significant in regressions for the sample period of 1963-1995. Second, MABA is insignificant in the pre-1995 period, which is consistent with the finding in Rubin and Smith (2011). This implies that the explanatory power of MABA comes mostly from the short period of time around year 2000. In contrast, the aggregate asset growth measure is still significant in this sub-sample, even when the episode around year 2000 is excluded.

4.2.2 Controlling for sentiment

Existing studies find that the cross-sectional return patterns related to the asset growth (Stambaugh, Yu, and Yuan (2012)) and idiosyncratic volatility (Stambaugh, Yu, and Yuan (2014)) are both affected by market-wide investor sentiment. Therefore, it is important to control for the investor sentiment when studying the relationship between asset growth and the average idiosyncratic volatility.

I follow Stambaugh, Yu, and Yuan (2012) and use the market-wide sentiment index from Baker and Wurgler (2006). Panel (b) of Table 5 reports the results. First, the sentiment measure is positively related to the average idiosyncratic volatility in the time series. However, the coefficient is insignificant and the R-square is low. Second, when the asset growth measure (HMLgA) is added to the regression, the sentiment loses all its explanatory power. However, the asset growth measure is still highly significant, with or without controlling for lagged idiosyncratic volatility. These results show that the asset growth effect on the average idiosyncratic volatility is unrelated to the investor sentiment.

4.2.3 Additional robustness checks

I consider three further robustness checks in the time series. To save space, I report only the findings of additional robustness analysis without tabulating the results. First, I repeat the analysis by using different time frequency of the volatility measure or the weighting method. Specifically, I show that the main findings reported in Section 4.1 still hold when monthly frequency of volatility is used. In addition, the asset growth dispersion also predicts positively the next year's average idiosyncratic volatility in the equal-weighted time series. Second, I consider four alternative measures of the volatility and two measures of the asset growth as discussed in Section 3.2. The main findings reported in Section 4.1 still hold. Finally, the asset growth effect on idiosyncratic volatility in the time series is robust after controlling for the past returns.

4.3 COMPARISONS WITH ALTERNATIVE TIME SERIES EXPLANATIONS

In this section, I compare the asset growth effect in the time series with two closely related alternative explanations: cash-flow volatility (Section 4.3.1) and growth options (Section 4.3.2). In addition, I run a horse race among the most significant explanations of the average IVol (Section 4.3.3). The purpose of the comparison is to show that the asset growth effect is independent of these alternatives and it has the strongest explanatory power in the time series.

4.3.1 Asset growth versus cash-flow volatility

Irvine and Pontiff (2009) study the effect of unexpected cash flow shocks on the average idiosyncratic volatility in the time series. They interpret the increasing cash flow volatility as a result of intensified competition among firms over time. Wei and Zhang (2006) use return-on-equity (ROE) and its time series variance (VROE) as the proxies cash-flow and its uncertainty to explain the aggregate idiosyncratic volatility.

As in the cross-sectional analysis, here I follow Wei and Zhang (2006)'s measures of cash flow (i.e., ROE) and volatility of cash flow (i.e., VROE). The time series results are reported in panel (c) of Table 5. Note that both the two cash-flow measures are insignificant in bivariate regression with both measures. Surprisingly, when the asset growth is controlled for, the VROE even turns from insignificant positive to significant negative. Note, however, the asset growth measure is highly significant and increase dramatically the R-square.

I conclude that the proxies of cash-flow and its volatility lack explanatory power in the time series, while the asset growth measure retains its high explanatory power.

4.3.2 Asset growth versus growth options

As reported in Table 4, MABA, which proxies growth options, is the only other variable that shows significant explanatory power in the time series. Cao, Simin, and Zhao (2008) use this measure to explain the aggregate return volatility. In this section, I make direct comparisons between the asset growth and the growth options measures.

Panel (d) of Table 5 reports the results when MABA and its variance VMABA are both used. First, the MABA has a robustness positive effect on the average idiosyncratic return volatility across different regressions (note the VMABA changed sign across regressions). Second, the asset growth measure is still highly significant even if we control the MABA. As I discussed in Section 4.1, the R-square of asset growth measure is much higher than that of the MABA. Overall, the asset growth measure is a better explanation of the average idiosyncratic volatility than the growth options measure.

4.3.3 Determinants of average idiosyncratic volatility: a horse race

As discussed in the Introduction, following Campbell, Lettau, Malkiel, and Xu (2001), there is a large empirical literature that tries to explain the time series of average idiosyncratic volatility. More recent studies try to summarize and compare the proposed explanations. For example, Zhang (2010) compares fundamentals-based with trading volume-based explanations of the average stock return volatility. He finds that much of the variation in the return volatility can be explained by fundamental variables, such as volatility of return on equity (VROE) and growth options (MABA), but not by trading-related variables. Bekaert, Hodrick, and Zhang (2012) run a horse race among 17 variables in order to determine which variables best capture the time series variation in the U.S. average idiosyncratic volatility. They find that the most important determinants of the average volatility are (i) the growth options variable (MABA) and (ii) the market-wide volatility. In addition, R&D expenditures also explain a nonnegligible part of the variation of the aggregate idiosyncratic volatility.

Since the asset growth measure is new to this literature, it's interesting to perform a similar comparison. As reported before (see, e.g., Table 4), the asset growth measure has a very strong explanatory power in the time series. Therefore, I only need to compare the asset growth with the existing variables that show significant explanatory power. Specifically, I follow the results in Bekaert, Hodrick, and Zhang (2012), and compare the asset growth measure with (i) the growth options variable (MABA), (ii) the volatility of the market index (MKTTV), and (iii) two R&D expenditures related variables (one is the value-weighted average R&D expenditures scaled by firms' sales (RD), and the other is the cross-sectional variance of RD (CVRD)).[18]

To compare the explanatory power of these alternative explanations of aggregate idiosyncratic volatility, I take two approaches. In the first approach, I run time series regressions of the aggregate idiosyncratic volatility on each individual explanations and compare the corresponding explanatory power in terms of R-square. In the second approach, I run multiple regressions that include all these variables. In this case the R-square measures the total contribution of the all variables. To gauge the relative importance of the various variables in explaining the variations in aggregate idiosyncratic volatility, I follow Bekaert, Hodrick, and Zhang (2012) and decompose the covariance of the fitted volatility. The covariance decomposition is intuitive and straightforward. Consider a multiple linear regression of y_t on explanatory variables x_{it}, with $i = 1, 2...n$. Denote the fitted value and the coefficients as $\hat{y_t}$ and $\hat{\beta}_i$ respectively. Then the contribution of variable x_i on the fitted variance is simply $\text{cov}(\hat{y_t}, \hat{\beta}_i x_{it})/\text{var}(\hat{y_t})$. These ratios add up to one by construction. With this covariance decomposition, we can compare directly the explanatory power of each explanations in multiple regressions.

Table 6 reports the results. I first compare the four explanations when each of them is used to explain the average idiosyncratic volatility. Panel (a) shows that, consistent

[18] Note that Bekaert, Hodrick, and Zhang (2012) also report three other variables (see their Table 6) that are significant in terms of t-statistics, but they all have negligible explanatory power in the time series (they only account for about 2% of variations in the aggregate idiosyncratic volatility). Note also that the market wide volatility is the volatility of the value-weighted index concurrent to the idiosyncratic volatility. In unreported analysis, I find that the lagged market volatility has a very small explanatory power once the lagged idiosyncratic volatility or the lagged asset growth is controlled for.

Table 6 Determinants of average idiosyncratic volatility: a horse race
The table reports the time series regressions of the value-weighted average idiosyncratic volatility on different explanatory variables from 1963 to 2013. The regressions have the following general form: $\overline{IVol_t} = \alpha + \beta_{gA} HMLgA_{t-1} + \beta_x X_{t-1} + \epsilon_t$. The dependent variable is the average idiosyncratic volatility ($\overline{IVol}$), which is calculated as the cross-sectional average idiosyncratic volatility for each year. The aggregate asset growth measure, denoted by HMLgA, is the difference in average asset growth rates between high-growth firms and low-growth firms, with the breaking annual asset growth rate of 5%. The regression may include the lagged average volatility (LagIVol) and other controlling variables (X_{t-1}). MKTTV is the total variance of the value-weighted market index. MABA is the average ratio of market assets to book assets. RD is the value-weighted average firm-level research and development expenditures scaled by sales (in percentage), and the CVRD is the corresponding cross-sectional variance. Panel (a) reports univariate regressions. Panel (b) performs the covariance decomposition and reports the variance explained by each variable as a percentage of total explained variance. DW is the Durbin Watson statistic. The t-statistics are calculated using Newey-West adjusted standard errors with a lag length of 2.

		LagIVol	HMLgA	MABA	MKTTV	RD	CVRD	DW	Adj. R^2 (%)
(a) Individual explanations									
(1)	Coeff.		0.525					2.01	57.50
	t-stat		(10.38)						
(2)	Coeff.			0.047				1.13	39.84
	t-stat			(4.30)					
(3)	Coeff.				1.176			0.53	50.94
	t-stat				(5.45)				
(4)	Coeff.					-3.594	0.012	0.50	20.58
	t-stat					(-1.24)	(6.17)		
(b) Multiple explanations with covariance decomposition									
(5)	Coeff.		0.362	0.012	0.740	-5.064	0.004	1.16	85.91
	t-stat		(5.76)	(1.81)	(2.75)	(-5.24)	(1.15)		
	Cov. decomp.		46%	12%	37%	-4%	9%		
(6)	Coeff.	0.159	0.299	0.011	0.714	-7.229	0.005	1.34	86.55
	t-stat	(1.06)	(4.07)	(1.85)	(2.86)	(-3.23)	(1.45)		
	Cov. decomp.	10%	38%	11%	35%	-6%	12%		

with earlier results, the asset growth measure (the asset growth dispersion HMLgA) has the highest R-square (57.5%). Confirming the findings in Bekaert, Hodrick, and Zhang (2012), the other two variables that show high explanatory power are market total variance (MKTTV) and growth options measure (MABA), with R-square of 50.9% and 39.8%, respectively. The two R&D measures (RD and CVRD) also have sizable explanatory power with R-square of 20.6%.

Panel (b) reports the multiple regressions with covariance decomposition. When all explanations are included (regression (5)), they explain around 86% of the variations in aggregate idiosyncratic volatility. In terms of t-statistics, both the asset growth, market total volatility, and RD are significant. In the covariance decomposition, the asset growth measure HMLgA accounts for 46% of the explained variance; the market volatility MKTTV accounts for 37%; the growth options measure MABA accounts for 12%; and the two RD measures account for 5% in net. Finally, I also add the lagged idiosyncratic volatility, LagIVol, in the full regression (6). The results are similar. In this case, the ordering of the explanations in terms of covariance decomposition is HMLgA (38%), MKTTV (35%), MABA (11%), LagIVol (10%), and RD measures (6%).

The results in Table 6 show that the asset growth measure is the winner of the time series race. Compared with other significant alternative explanations, the asset growth measure has the highest explanatory power in explaining the time series of average idiosyncratic volatility.

5 Conclusion

This paper documents the empirical relationship between asset growth rate and stock return volatility. In the cross-section, the idiosyncratic return volatility shows a V-shaped relationship with asset growth rate. That is, stocks with either high positive or negative asset growth rates have high idiosyncratic return volatility. In the time series, a higher cross-sectional dispersion of the firm-level asset growth rate predicts a higher average idiosyncratic return volatility.

This paper further documents the robustness of these empirical findings. First, the V-shaped relationship in the cross-section is robust even after controlling for factors such as size and cash flow volatility. Second, the asset growth effect on idiosyncratic return volatility empirically dominates alternative explanations of idiosyncratic return volatility such as cash flow and its volatility, growth options, and forecasted long-term earnings growth. Finally, the asset growth measure is the most important predictor of the average idiosyncratic return volatility in the time series.

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