Review of Financial Economics 35 (2017) 11–28

Contents lists available at ScienceDirect

Review of Financial Economics

journal homepage: www.elsevier.com/locate/rfe

Trend in aggregate idiosyncratic volatility

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ARTICLE INFO

Article history:
Received 19 June 2016
Received in revised form 30 October 2016
Accepted 1 November 2016
Available online 9 November 2016

JEL classification:
G10
G12

Keywords:
Idiosyncratic return volatility
Price interaction
Small firm effect

ABSTRACT

We suggest that price interaction among stocks is an important determinant of idiosyncratic volatility. We demonstrate that as more (less) stocks are listed in the markets, price interaction among stocks increases (decreases), and hence stocks, on average, become more (less) volatile. Our results show that price interaction has a significant positive effect of idiosyncratic volatility. The results of various robustness checks indicate that the effect of price interaction is still significant to the presence of liquidity, newly listed firms, cash flow variables, business cycle variables, and market volatility. Once the price interaction effect is taken into account, no trend remains in idiosyncratic volatility. We conclude that there is no trend, but a reflection of the positive effect of price interaction on idiosyncratic volatility.

1. Introduction

In a seminal paper, Campbell, Lettau, Malkiel, and Xu (2001) find that aggregate idiosyncratic volatility exhibits a deterministic time trend through the late 1990s, while market volatility and industry volatilities remain roughly constant during this time. This finding has led to a series of research regarding the importance of idiosyncratic volatility for asset pricing and portfolio management.[1]

A substantial body of literature has attempted to explain the time-series behavior of aggregate idiosyncratic volatility. One line of studies proposes that a change in idiosyncratic cash flow variability contributes to the time variation in aggregate idiosyncratic volatility. Given that stock price is driven by both systematic discount factor and idiosyncratic cash flow, these studies argue that it is the time-varying determinants of firm-specific cash flow that cause the time trend of aggregate idiosyncratic volatility. Comin and Mulani (2006) address the role of R&D in shaping idiosyncratic volatility while Guo and Savickas (2008) link changes in aggregate idiosyncratic volatility to changes in the investment opportunity set related to the book-to-market factor. Cao, Simin, and Zhao (2008) find that corporate growth options explain the trend in aggregate idiosyncratic volatility. Moreover, Wei and Zhang (2006) argue that the aggregate idiosyncratic volatility trend is attributable to deteriorating earnings quality. Both Irvine and Pontiff (2009) and Gaspar and Massa (2006) suggest that increased competition in the product markets contributes to an increase in aggregate idiosyncratic volatility.

In addition, a set of studies focuses on the role of heterogeneous investors. Bennett, Sias, and Starks (2003) and Xu and Malkiel (2003) argue that the trend can be attributed to increased institutional ownership, especially the increased preference by institutions for small stocks. Foucault, Sraer, and Thesmar (2011) confirm that a change in individual investor participation affects a level of aggregate idiosyncratic volatility. Several studies relate the time variation in aggregate idiosyncratic volatility to the time-varying composition of the market portfolio. Brown and Kapadia (2007) attribute the time trend in aggregate idiosyncratic volatility to the increase in new listings of riskier firms. Fink, Fink, Grullon, and Weston (2010) also find that this increasing trend is consistent with an increase in new listings and, as a result, with a decline in the maturity of typical public firms in the market.

By providing evidence of a sharp downturn in aggregate idiosyncratic volatility in the 2000s following a significant positive trend in the 1990s, Brandt, Brav, Graham, and Kumar (2010) argue that the observed upward and downward patterns of deterministic trends are attributed to retail investors' trading patterns on low-priced stocks. Their finding of a negative volatility trend during the 2000s, though used as evidence against the time trend, pose a serious challenge to

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[1] See, Bali, Cakici, and Whitelaw (2011), Ang, Hodrick, Xing, and Zhang (2006, 2009), Bali and Cakici (2008), Aktas, De Bodt, and Cousin (2009), Comin and Mulani (2006), Bali, Cakici, Yan, and Zhang (2005), Kothari and Warner (2004), and Xu and Malkiel (2003).

http://dx.doi.org/10.1016/j.rfe.2016.11.001
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existing hypotheses that are primarily concerned with the positive trend in idiosyncratic volatility. Credible theories concerning this issue should now be able to explain the trends in both positive and negative directions.

In this paper, we suggest that price interaction among stocks plays an important role in generating the time variation in aggregate idiosyncratic volatility. Stocks covary with each other such that changes in stock prices cause price changes in other stocks. As more stocks are listed in the markets, investors have access to more choices of stocks for trading. Consequently, when stock prices change, more stocks are likely to follow suit in either directions, causing higher co-movements in stock prices, which in turn increases idiosyncratic volatility.[2] We suggest that as more (less) stocks are listed in the markets, price interaction among stocks increases (decreases), and hence increasing (decreasing) co-movements in stock prices. Thus, as more (less) stocks are listed in the markets, stocks become more (less) volatile, ceteris paribus. Therefore, the trend in idiosyncratic volatility is the aggregate reflection of the price interaction effect on return volatility.

This paper is motivated by the observation that the significant positive (negative) trend in the aggregate idiosyncratic volatility from 1963.07 to 2000.04 (2000.05 to 2008.09) identified by Brandt et al. (2010) coincides with the similar significant increase (decrease) in the number of listed firms over the two periods. The plots (a) and (b) of Fig. 1 show the level of monthly equal- and value-weighted aggregate idiosyncratic volatility in square root, while the plots (c) shows the number of firms that is included in computing the aggregate average idiosyncratic volatility in each month over the 1963.07–2008.09 sample period. The plots indicate that the U.S. stock markets during 1990s (2000s) is characterized by an upward (downward) trend in aggregate idiosyncratic volatility with a persistent increase (a sharp drop) in the number of firms listed in the markets for the sample periods. The plots suggest that there is an important link between the trends in aggregate idiosyncratic volatility and the price co-movements from interaction among stock prices.[3]

To illustrate our arguments, let's consider a town where the level of social activities per capita exhibits a steady increase for some time period and a sharp decline thereafter. Of course, there are many economic and social factors that induce peoples' social activities over time. It is, however, reasonable to consider population size of the town as a fundamental factor to induce the observed trend patterns in the level of social activities. As the town's population increases (decreases), social interactions among people increase (decrease). An increase (decrease) in social interactions per person induces more (less) social activities per person. Consequently, the trend might be attributed to the effect of the town's population size on the social interactions among the inhabitants over time.

We apply the same logic to explain the variation patterns in aggregate idiosyncratic volatility. Stocks covary with each other, such that changes in stock prices cause price changes in other stocks. As more stocks are listed in the markets, additional stocks are included in the category of the same or a related industry, a competing business, or a related business. As such, investors have access to more choices of stocks for trading. Thus, when stock prices change, stocks are more likely to follow suit in either direction, increasing the level of idiosyncratic volatility.

In estimations, we employ the number of listed stocks as the proxy for price interaction among stocks. Our estimation results indicate that price interaction among stocks has significant explanatory power for the time variation in aggregate idiosyncratic volatility. There are several notable findings. First, there is a significant positive effect of price interaction among stocks on aggregate idiosyncratic volatility from 1926.07 to 2014.12 in U.S. stock markets, and a substantial portion of time variation in aggregate idiosyncratic volatility is explained by this positive effect. The results indicate that the price interaction effect is still robust to the existing explanatory variables, such as liquidity, newly listed firms, cash flow variables, business cycle variables, and market volatility.

The observed pattern of positive and negative time trends in aggregate idiosyncratic volatility can be explained by the positive effect of price interaction on return volatility. The estimation results indicate that a steady increase in the number of stocks listed in the markets prior to the late 1990s caused stocks to be more volatile due to the increased price interaction among stocks, thereby inducing a positive trend in idiosyncratic volatility. Likewise, the steep negative trend during the 2000s is attributed to a sharp decline in the number of listed firms during this period, which considerably reduced the level of price interaction among stocks inducing a negative trend in aggregate idiosyncratic volatility.

Moreover, there is a significant firm-size effect in the level of price interaction among the size portfolios, which is observed in the level of volatility reported by Bennett et al. (2003), Xu and Malkiel (2003), and Brandt et al. (2010). Our estimation results regarding the ten size decile portfolios indicate that the level of price co-movements from interaction among stock prices increases monotonically as the size decreases. As such, the smallest (largest) size decile portfolio exhibits the greatest (smallest) level of price interaction. More importantly, for all ten size decile portfolios, the positive and negative pattern of trends in idiosyncratic volatility completely disappears under the positive effect of price interaction on return volatility. These results support our argument that price interaction among stock prices is a key determinant for the time variation of idiosyncratic volatility.

Our paper proceeds as follows. In Section 2, we present four empirical implications of the price interaction hypothesis. In Section 3, we report the estimation results for aggregate idiosyncratic volatility with various robustness checks. In Section 4, we provide the estimation results for the individual stocks' idiosyncratic volatility. In Section 5, we present the estimation results for the size effect, while Section 6 provides our conclusion.

2. Price interaction hypothesis

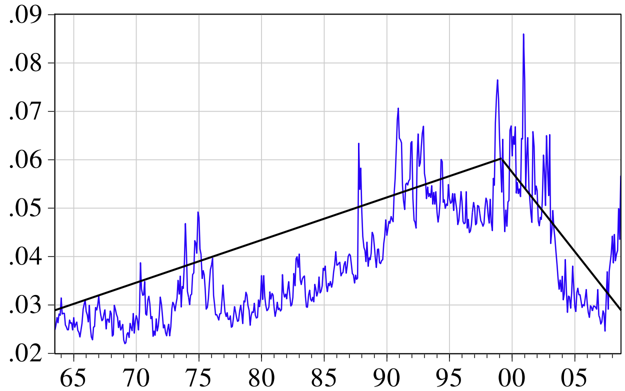
Although the direct measure of price interaction among stocks is practically not available, it is well known that stocks covary with each other. As more stocks are available in the markets, the number of pairwise interactions among stocks, i.e., ${}_NC_2 = N(N-1)/2$, increases at a faster growth rate than the growth rate of the number of stocks. Thus, price interaction is a positive monotonic function of the number of stocks. We thus employ the number of listed firms in the markets as the proxy for price interaction among stocks.

We examine the effect of price interaction on aggregate idiosyncratic volatility by taking a derivative of the number of listed firms on aggregate average idiosyncratic variance that is derived from the relationship between portfolio variance and the individual stock's variance. Consider the following simple market model for the i^{th} stock:

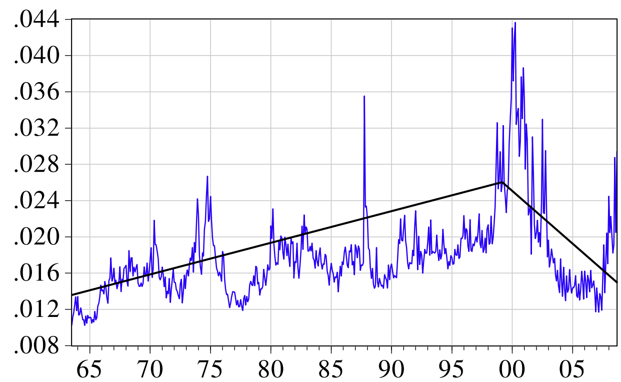
$$r_{i,t} = \alpha + \beta_i r_{M,t} + \varepsilon_{i,t}, \tag{1}$$

[2] The volatility feedback effect could be one of the channels to induce price co-movements among stocks. As more stocks are listed in the markets, volatility feedback among stocks increases, thereby making stocks relatively more volatile.

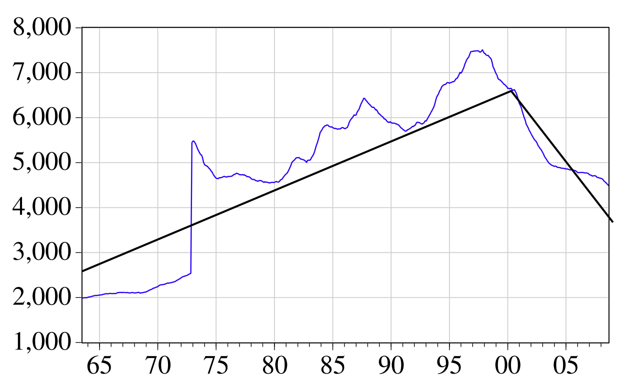
[3] The annual average growth rate in the number of firms listed in the markets was 4.87% until 1997, but it was −4.13% from 1997 to 2008. Following Brandt et al. (2010), we choose 2000.04 as the single breakpoint in trend line. The two trend lines in the aggregate average idiosyncratic volatility plots are based on the estimated trend coefficient from the trend regressions of equations (16) for the 1963.07–2000.04 period and the 2000.05–2008.09 period, respectively. The two trend lines in the number of firms are based on the estimated trend coefficient from the trend regressions on the number of firms. The estimated value of trend coefficient is 12.82 for the 1963.07–2000.04 period and −18.22 for the 2000.05–2008.09 period.



(a) The Level of Monthly Equal-Weighted Aggregate Idiosyncratic Volatility



(b)The Level of Monthly Value-Weighted Aggregate Idiosyncratic Volatility



(c) Number of Firms Listed in the NYSE, AMEX, and NASDAQ Markets

Fig. 1. Monthly aggregate average idiosyncratic volatility and number of firms (a) The level of monthly equal-weighted aggregate idiosyncratic volatility (b) The level of monthly value-weighted aggregate idiosyncratic volatility (c) Number of firms listed in the NYSE, AMEX, and NASDAQ markets.

where $r_{i,t}$ and $\varepsilon_{i,t}$ are the returns and the idiosyncratic residuals, respectively, of stock i. The unconditional variance (σ_i^2) of $r_{i,t}$ can be expressed as follows:

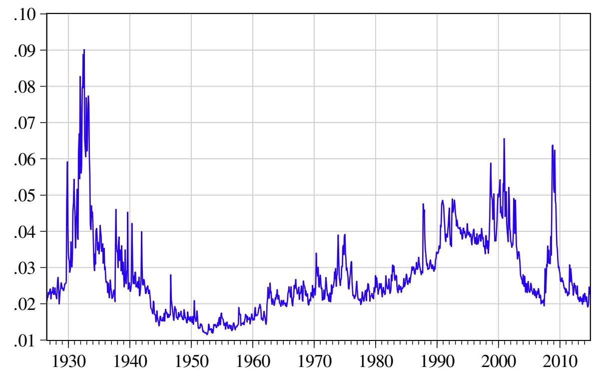
$$\sigma_i^2 = \beta_i^2\sigma_M^2 + \sigma_{iv}^2, \tag{2}$$

where σ_M^2 is the unconditional variance of the market portfolio and σ_{iv}^2 is the idiosyncratic variance of stock i. Summing all of the individual unconditional variances of N stocks, we obtain the total aggregate idiosyncratic variance as follows:

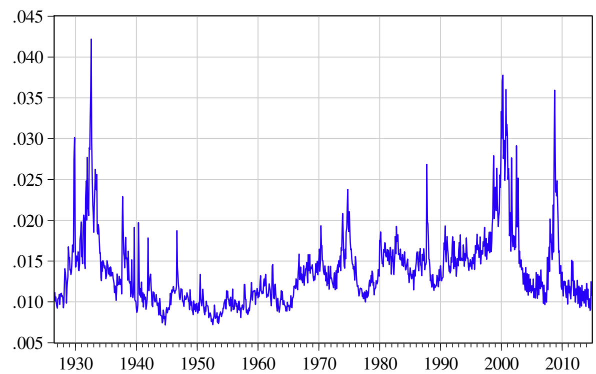
$$\sum\sigma_{iv}^2 = \sum\sigma_i^2 - \sum\beta_i^2\sigma_M^2. \tag{3}$$

Multiplying both sides of Eq. (3) by $1/N$ yields the followings:

$$\frac{\sum\sigma_{iv}^2}{N} = \frac{\sum\sigma_i^2}{N} - \frac{\sum\beta_i^2}{N}\sigma_M^2. \tag{4}$$



(a) The Level of Equal-Weighted Aggregate Average Idiosyncratic Volatility



(b) The Level of Value-Weighted Aggregate Average Idiosyncratic Volatility

Fig. 2. Monthly aggregate average idiosyncratic volatility (a) The level of equal-weighted aggregate average idiosyncratic volatility (b) The level of value-weighted aggregate average idiosyncratic volatility.

Table 1
Interaction regression on aggregate average volatility.

	Equal-weighted aggregate average idiosyncratic volatility				Value-weighted aggregate average idiosyncratic volatility			
	1926.07–2014.12	1945.01–2014.12	1945.01–2000.04	2000.05–2014.12	1926.07–2014.12	1945.01–2014.12	1945.01–2000.04	2000.05–2014.12
Aggregate average idiosyncratic volatility computed from the simple CAPM model								
$\delta(\times 10^6)$	1.88	3.73	3.54	8.03	0.83	1.30	1.16	5.05
	(4.78)	(18.53)	(18.17)	(7.65)	(5.18)	(9.23)	(9.75)	(6.95)
$\overline{R}^2(\%)$	12.89	61.53	72.07	33.60	15.13	36.25	44.91	41.82
Aggregate average idiosyncratic volatility computed from the augmented CAPM model								
$\delta(\times 10^6)$	1.90	3.71	3.53	7.93	0.82	1.28	1.15	4.94
	(4.90)	(18.72)	(18.27)	(7.73)	(5.28)	(9.34)	(9.89)	(6.83)
$\overline{R}^2(\%)$	13.61	62.28	72.66	34.11	15.85	37.16	46.36	41.90
Aggregate average idiosyncratic volatility computed from Fama–French 3-factor model								
$\delta(\times 10^6)$	1.91	3.71	3.53	8.03	0.79	1.24	1.11	4.93
	(4.97)	(18.72)	(18.32)	(7.85)	(5.21)	(9.34)	(10.00)	(7.12)
$\overline{R}^2(\%)$	13.95	62.51	72.79	35.24	15.67	37.76	47.48	44.62
Aggregate average unconditional standard deviation								
$\delta(\times 10^6)$	1.59	3.64	3.39	7.38	0.68	1.14	1.25	5.21
	(3.66)	(16.62)	(16.25)	(5.88)	(2.86)	(8.22)	(8.15)	(5.60)
$\overline{R}^2(\%)$	7.45	52.77	66.02	21.45	4.18	24.15	31.33	20.56

This table reports the estimation results of the interaction regression between the realized aggregate average idiosyncratic volatility and the number of firms. The interaction parameter δ measures the effect of price interaction on aggregate idiosyncratic volatility. As the measure of the aggregate average idiosyncratic volatility, we employ the root mean square error (RMSE) estimated from the simple capital asset pricing model, the augmented capital asset pricing model, and the Fama–French three factor model. We also report the estimation results of the interaction regression between the aggregate average unconditional standard deviation and the number of firms. The Newey and West (1987) adjusted t-statistics under the Bartlett kernel with the Newey and West (1987) fixed bandwidth are presented in parentheses below the coefficient estimate. $\overline{R}^2(\%)$ is the adjusted R^2 in percentage.

Table 2
Price interaction under liquidity effect.

	Equal-weighted aggregate average idiosyncratic volatility								Value-weighted aggregate average idiosyncratic volatility							
	1926.07–2014.12		1945.01–2014.12		1945.01–2000.04		2000.05–2014.12		1926.07–2014.12		1945.01–2014.12		1945.01–2000.04		2000.05–2014.12	
	LQ1	LQ2	LQ1	LQ2	LQ1	LQ2	LQ1	LQ2	LQ1	LQ2	LQ1	LQ2	LQ1	LQ2	LQ1	LQ2
Aggregate average idiosyncratic volatility computed from the simple CAPM model																
$\delta(\times 10^6)$		3.37		3.74		3.50		2.89		1.22		1.30		1.17		2.95
		(15.66)		(19.11)		(18.47)		(2.08)		(8.85)		(9.08)		(9.58)		(2.78)
γ	3.97	5.71	4.51	4.53	5.12	3.47	31.06	27.31	0.87	1.50	0.82	0.82	0.03	−0.52	14.99	11.16
	(9.29)	(21.61)	(2.81)	(4.34)	(2.47)	(2.87)	(10.45)	(7.08)	(3.88)	(10.68)	(1.09)	(1.36)	(0.03)	(−0.56)	(7.76)	(4.80)
$\overline{R}^2(\%)$	28.85	64.73	3.33	64.97	4.16	74.00	73.54	76.75	8.33	36.77	0.43	36.74	−0.15	45.08	53.57	64.30
Aggregate average idiosyncratic volatility computed from the augmented CAPM model																
$\delta(\times 10^6)$		3.35		3.71		3.48		2.89		1.20		1.28		1.16		2.91
		(15.92)		(19.32)		(18.58)		(2.14)		(9.00)		(9.20)		(9.73)		(2.77)
γ	3.87	5.60	4.47	4.48	5.07	3.43	30.53	26.77	0.84	1.47	0.74	0.75	−0.02	−0.57	14.58	10.81
	(9.15)	(21.72)	(2.79)	(4.33)	(2.45)	(2.85)	(10.64)	(7.17)	(3.78)	(10.63)	(1.00)	(1.25)	(−0.02)	(−0.62)	(7.78)	(4.81)
$\overline{R}^2(\%)$	28.53	65.55	3.35	65.73	4.16	74.58	73.94	77.30	8.32	37.80	0.36	37.57	−0.15	46.60	53.05	63.95
Aggregate average idiosyncratic volatility computed from Fama–French 3-factor model																
$\delta(\times 10^6)$		3.35		3.71		3.48		3.03		1.17		1.24		1.12		2.98
		(15.99)		(19.35)		(18.68)		(2.25)		(9.02)		(9.18)		(9.82)		(2.96)
γ	3.83	5.56	4.58	4.60	5.12	3.48	30.47	26.53	0.85	1.45	0.87	0.88	0.08	−0.44	14.23	10.36
	(9.09)	(21.92)	(2.87)	(4.41)	(2.48)	(2.88)	(10.83)	(7.24)	(3.83)	(10.30)	(1.22)	(1.53)	(0.08)	(−0.51)	(8.15)	(5.08)
$\overline{R}^2(\%)$	28.37	65.90	3.56	66.18	4.25	74.77	74.24	77.98	9.06	38.80	0.60	38.41	−0.14	47.62	53.99	66.28
Aggregate average unconditional standard deviation																
$\delta(\times 10^6)$		3.21		3.64		3.33		1.14		1.35		1.47		1.25		1.37
		(13.54)		(17.19)		(16.43)		(0.66)		(7.30)		(8.10)		(7.87)		(0.93)
γ	4.58	6.24	4.42	4.44	5.50	3.93	34.63	33.15	1.88	2.58	1.26	1.27	0.88	0.29	22.19	20.41
	(10.70)	(19.23)	(2.75)	(4.02)	(2.73)	(3.22)	(8.44)	(6.38)	(6.59)	(12.65)	(1.33)	(1.57)	(0.67)	(0.26)	(7.22)	(5.12)
$\overline{R}^2(\%)$	31.37	57.98	2.88	55.74	4.84	68.50	69.77	70.00	16.35	30.87	0.57	24.76	0.29	31.27	55.01	55.86

This table reports the estimation results of the interaction regression between the realized aggregate average idiosyncratic volatility and the number of firms. The interaction parameter δ measures the effect of price interaction on aggregate idiosyncratic volatility, while γ captures the effect of each control variable on aggregate idiosyncratic volatility. As the measure of the aggregate average idiosyncratic volatility, we employ the root mean square error (RMSE) estimated from the simple capital asset pricing model, the augmented capital asset pricing model, and the Fama–French three factor model. We also report the estimation results of the interaction regression between the aggregate average unconditional standard deviation and the number of firms. The Newey and West (1987) adjusted t-statistics under the Bartlett kernel with the Newey and West (1987) fixed bandwidth are presented in parentheses below the coefficient estimate. $\overline{R}^2(\%)$ is the adjusted R^2 in percentage.

Let $\sigma_{IV}^2 = \frac{\sum \sigma_{iv}^2}{N}$ and $\sigma_{UV}^2 = \frac{\sum \sigma_i^2}{N}$. Then, Eq. (4) can be rewritten as follows:

$$\sigma_{IV}^2 = \sigma_{UV}^2 - \frac{\sum \beta_i^2}{N}\sigma_M^2 = \sigma_{UV}^2 - \frac{\sum [\sigma_{iM}]^2}{N\sigma_M^2}, \tag{5}$$

where σ_{IV}^2 is the equal-weighted aggregate idiosyncratic variance and σ_{UV}^2 is the average unconditional variance of N stocks. σ_{iM} is the return covariance between stock i and the market portfolio. Using the partial derivative of aggregate idiosyncratic variance with respective to N, we obtain the followings:

$$\frac{\partial \sigma_{IV}^2}{\partial N} = \frac{\partial \sigma_{UV}^2}{\partial N} + \frac{\sum [\sigma_{iM}]^2}{N^2 \sigma_M^2}, \tag{6}$$

where the sign of Eq. (6) depends upon the sign of $\frac{\partial \sigma_{UV}^2}{\partial N}$. To determine the sign of $\frac{\partial \sigma_{UV}^2}{\partial N}$, we first consider the variance of the equal-weighted portfolio returns with two stocks as follow:

$$\sigma_{EW}^2 = \frac{1}{4}\sigma_1^2 + \frac{1}{4}\sigma_2^2 + \frac{1}{2}\sigma_{12} = \frac{1}{2}\left(\frac{1}{2}\sigma_1^2 + \frac{1}{2}\sigma_2^2 + \sigma_{12}\right)$$
$$= \frac{1}{2}\left(\sigma_{UV}^2 + \sigma_{12}\right), \tag{7}$$

where σ_{UV}^2 is the simple average of the two unconditional variances, σ_1^2 and σ_2^2, and σ_{12} is the covariance between Stocks 1 and 2. We can rewrite Eq. (7) as follows:

$$\sigma_{UV}^2 = 2\sigma_{EW}^2 - \sigma_{12}, \tag{8}$$

Second, with three stocks, the variance of the equal-weighted portfolio returns is given by:

$$\sigma_{EW}^2 = \frac{1}{9}\sum_i^3 \sigma_i^2 + \frac{2}{9}\sum_i^{i\neq j}\sigma_{ij} = \frac{1}{3}\left(\frac{1}{3}\sum_i^3 \sigma_i^2 + \frac{2}{3}\sum_i^{i\neq j}\sigma_{ij}\right)$$
$$= \frac{1}{3}\left(\sigma_{UV}^2 + \frac{2}{3}\sum_i^{i\neq j}\sigma_{ij}\right). \tag{9}$$

We can rewrite Eq. (9) as follows:

$$\sigma_{UV}^2 = 3\sigma_{EW}^2 - \frac{2}{3}\sum_i^{i\neq j}\sigma_{ij}. \tag{10}$$

Then, for N stocks the variance of the equal-weighted portfolio returns can be expressed as follows:

$$\sigma_{EW}^2 = \sigma_M^2 = \frac{1}{N^2}\sum_i^N \sigma_i^2 + \frac{2}{N^2}\sum_i^{i\neq j}\sigma_{ij} = \frac{1}{N}\left(\frac{1}{N}\sum_i^N \sigma_i^2 + \frac{2}{N}\sum_i^{i\neq j}\sigma_{ij}\right)$$
$$= \frac{1}{N}\left(\sigma_{UV}^2 + \frac{2}{N}\sum_i^{i\neq j}\sigma_{ij}\right). \tag{11}$$

Rewriting Eq. (11), we obtain the aggregate average unconditional variance for N stocks as follows:

$$\sigma_{UV}^2 = N\sigma_M^2 - \frac{2}{N}\sum_i^{i\neq j}\sigma_{ij}, \tag{12}$$

Table 3
Price interaction under the effect of newly listed firms.

	Equal-weighted aggregate average idiosyncratic volatility								Value-weighted aggregate average idiosyncratic volatility							
	1926.07–2014.12		1945.01–2014.12		1945.01–2000.04		2000.05–2014.12		1926.07–2014.12		1945.01–2014.12		1945.01–2000.04		2000.05–2014.12	
	NLF1	NLF2	NLF1	NLF2	NLF1	NLF2	NLF1	NLF2	NLF1	NLF2	NLF1	NLF2	NLF1	NLF2	NLF1	NLF2
Aggregate average idiosyncratic volatility computed from the simple CAPM model																
$\delta(\times 10^6)$		1.88		3.73		3.55		3.94		0.83		1.30		1.17		3.57
		(4.78)		(18.73)		(18.14)		(2.17)		(5.20)		(9.31)		(9.71)		(3.00)
$\gamma(\times 10^6)$	−0.68	−0.71	−0.61	−0.62	0.25	−0.27	−37.45	−28.72	−0.34	−0.35	−0.33	−0.33	0.35	−0.14	−18.78	−10.05
	(−1.34)	(−1.81)	(−1.22)	(−1.94)	(0.82)	(−2.81)	(−8.45)	(−3.63)	(−1.35)	(−1.75)	(−1.32)	(−1.80)	(0.47)	(−3.38)	(−6.50)	(−2.37)
$\overline{R}^2(\%)$	0.20	13.10	0.30	61.92	−0.06	72.14	44.13	49.10	0.34	15.48	0.46	36.76	−0.14	44.99	34.71	47.99
Aggregate average idiosyncratic volatility computed from the augmented CAPM model																
$\delta(\times 10^6)$		1.90		3.71		3.54		3.93		0.82		1.28		1.15		3.51
		(4.91)		(18.73)		(18.24)		(2.23)		(5.30)		(9.41)		(9.84)		(3.04)
$\gamma(\times 10^6)$	−0.67	−0.70	−0.60	−0.61	0.24	−0.27	−36.80	−27.19	−0.33	−0.34	−0.32	−0.32	0.41	−0.13	−18.29	−9.70
	(−1.34)	(−1.81)	(−1.22)	(−1.95)	(0.82)	(−2.95)	(−8.55)	(−3.66)	(−1.33)	(−1.73)	(−1.30)	(−1.78)	(0.43)	(−3.25)	(−6.33)	(−2.37)
$\overline{R}^2(\%)$	0.20	13.83	0.29	61.66	−0.06	72.73	44.36	49.53	0.34	16.20	0.44	37.66	−0.14	46.43	34.45	47.90
Aggregate average idiosyncratic volatility computed from Fama–French 3-factor model																
$\delta(\times 10^6)$		1.91		3.71		3.54		4.04		0.79		1.24		1.12		3.56
		(4.97)		(18.93)		(18.30)		(2.29)		(5.23)		(9.43)		(9.96)		(3.13)
$\gamma(\times 10^6)$	−0.68	−0.71	−0.62	−0.62	0.22	−0.29	−36.95	−27.07	−0.32	−0.33	−0.31	−0.31	0.35	−0.13	−18.02	−9.30
	(−1.38)	(−1.88)	(−1.26)	(−2.03)	(0.75)	(−3.07)	(−8.58)	(−3.66)	(−1.34)	(−1.74)	(−1.31)	(−1.80)	(0.39)	(−3.38)	(−6.77)	(−2.37)
$\overline{R}^2(\%)$	0.22	14.17	0.31	61.91	−0.08	72.88	45.11	50.65	0.34	16.02	0.46	38.28	−0.14	47.56	35.72	50.53
Aggregate average unconditional standard deviation																
$\delta(\times 10^6)$		1.59		3.64		3.40		2.64		0.68		1.47		1.26		2.64
		(3.66)		(16.80)		(16.21)		(1.18)		(2.87)		(8.31)		(8.13)		(1.54)
$\gamma(\times 10^6)$	−0.68	−0.81	−0.71	−0.71	0.22	−0.27	−38.69	−32.24	−0.55	−0.56	−0.52	−0.52	−0.39	−0.19	−23.92	−17.46
	(−1.34)	(−1.73)	(−1.25)	(−1.84)	(0.78)	(−2.73)	(−7.12)	(−3.40)	(−1.46)	(−1.66)	(−1.38)	(−1.71)	(−0.04)	(−3.38)	(−5.82)	(−2.56)
$\overline{R}^2(\%)$	0.20	7.68	0.38	53.22	−0.08	66.08	35.86	37.30	0.39	4.56	0.64	24.83	−0.15	31.40	26.23	29.30

This table reports the estimation results of the regression (NLF1) of the four aggregate volatility series on the number of monthly newly listed firms. This table also provides the estimation results of the interaction regressions (NLF2) for the four aggregate volatility series, with the number of newly listed firms as a control variable. The interaction parameter δ measures the effect of price interaction on aggregate idiosyncratic volatility, while γ captures the effect of newly listed firms on aggregate idiosyncratic volatility. The number of newly listed firms is computed as the first difference of the number of all the firms listed in the NYSE, AMEX, and NASDAQ markets. Note that we manipulate the data of the number of newly listed firms for subperiods, such that all of the negative observations for the sample period of 1945.01–2000.04 are changed to zero, while all of the positive observations are treated as zero for the sample period 2000.05–2014.12. The Newey and West (1987) adjusted t-statistics under the Bartlett kernel with the Newey–West fixed bandwidth are presented in parentheses below the coefficient estimate. $\overline{R}^2(\%)$ is the adjusted R^2 in percentage.

where $\sum_{i}^{i\neq j}\sigma_{ij}$ is the total covariance of N stocks. The partial derivative of σ^2_{UV} with respective to N is:

$$\frac{\partial\sigma^2_{UV}}{\partial N} = \sigma^2_M + \frac{2}{N^2}\sum_{i}^{i\neq j}\sigma_{ij}. \tag{13}$$

From the positivity condition of σ^2_M, i.e., $0<\sigma^2_M>\frac{2}{N^2}\sum_{i}^{i\neq j}\sigma_{ij}$, the sign of $\frac{\partial\sigma^2_{UV}}{\partial N}$ is always positive. The positive sign of $\frac{\partial\sigma^2_{UV}}{\partial N}$ implies that as N increases (decreases), individual stocks are on average more (less) volatile due to increased price interaction. More importantly, Eq. (6) indicates that the sign of $\frac{\partial\sigma^2_{IV}}{\partial N}$ is determined by the sign of $\frac{\partial\sigma^2_{UV}}{\partial N}$. As such, $\frac{\partial\sigma^2_{UV}}{\partial N}>0$ is the necessary condition for $\frac{\partial\sigma^2_{IV}}{\partial N}>0$. Also, for the range of $2000 < N < 8000$ in the U.S. equity markets, the magnitude of $\frac{\sum[\sigma_{iM}]^2}{N^2\sigma^2_M}$ in Eq. (6) is negligible, indicating that $\frac{\partial\sigma^2_{UV}}{\partial N}$ is the main component of $\frac{\partial\sigma^2_{IV}}{\partial N}$. The partial derivative of σ^2_{EW} with respect to N is $\frac{\partial\sigma^2_{EW}}{\partial N} = -\frac{1}{N^2}\left[\frac{\partial\sigma^2_{UV}}{\partial N} + \frac{4}{N}\sum_{i}^{i\neq j}\sigma_{ij}\right]$.

The result of $\frac{\partial\sigma^2_{UV}}{\partial N}>0$ and $\frac{\partial\sigma^2_{IV}}{\partial N}>0$ supports our hypothesis that as more (less) stocks are listed in the markets, the price interaction among stocks increases (decreases) and stocks, on average, become more (less) volatile. If our hypothesis is correct, then there are four testable implications on idiosyncratic volatility:

Implication #1: Price interaction among stocks has a positive effect on aggregate idiosyncratic volatility.

Implication #2: The observed trend pattern(s) in aggregate idiosyncratic volatility is attributed to the positive effect of price interaction on aggregate volatility.

Implication #3: Since aggregate idiosyncratic volatility is the weighted sum of individual idiosyncratic volatility, the price interaction effect should also be observed in the individual idiosyncratic volatility.

Implication #4: Since the price interaction effect is a trading-related phenomenon, there should be a size effect in the price interaction effect.

3. The estimations

3.1. Data and aggregate average idiosyncratic volatility

We collect stock returns from the CRSP data files and corporate variables from Compustat for U.S. listed stocks. We retrieve daily returns of all of the firms listed on the NYSE, AMEX and NASDAQ from 1926.07 to 2014.12. To compute the individual stock's monthly idiosyncratic volatility, we run three different asset pricing models: (a) the simple CAPM, (b) the augmented CAPM with a lag length four, and (c) the Fama–French 3-factor model on firms' daily returns within each month. We use the one month US T-bill rate reported by Ibbotson Associates as the risk-free rate. We construct the daily risk-free rate by assuming that it is constant within a month. The daily excess market portfolio return is the

Table 4
Interaction regression with other control variables.

	Equal-weighted aggregate average idiosyncratic volatility							Value-weighted aggregate average idiosyncratic volatility						
	ROA	MTB	RND	GIP	DEF	TMV	Joint	ROA	MTB	RND	GIP	DEF	TMV	Joint
Aggregate average idiosyncratic volatility computed from the simple CAPM model														
δ	4.76	3.95	5.21	5.08	2.38	2.14	6.11	1.77	0.95	2.40	1.89	0.99	0.93	1.96
$(\times 10^6)$	(8.42)	(7.05)	(6.41)	(8.71)	(8.45)	(6.75)	(13.58)	(4.66)	(3.24)	(4.35)	(4.80)	(7.32)	(6.84)	(11.07)
γ_{ROA}	−0.53						−0.41	−0.19						−0.12
	(−2.59)						(−2.67)	(−1.34)						(−1.64)
γ_{MTB}		0.24					0.16		0.21					0.25
$(\times 10^2)$		(5.71)					(3.98)		(6.94)					(10.93)
γ_{RND}			0.57				−0.35			1.07				0.12
$(\times 10^2)$			(0.97)				(−0.96)			(1.83)				(0.63)
γ_{GIP}				−0.13			−0.06				−0.07			−0.04
$(\times 10^2)$				(−2.64)			(−1.92)				(−2.88)			(−2.54)
γ_{DEF}					1.12		1.31					0.35		0.56
$(\times 10^2)$					(8.75)		(12.11)					(9.19)		(10.33)
γ_{TMV}						0.62	0.43						0.25	0.36
						(10.80)	(4.37)						(6.99)	(4.13)
$\bar{R}^2$(%)	37.53	42.96	36.38	36.25	55.91	35.79	72.96	19.13	41.99	24.13	19.45	40.98	37.93	80.67
Aggregate average idiosyncratic volatility computed from the augmented CAPM model														
δ	4.75	3.97	5.21	5.07	2.39	2.14	6.11	1.74	1.86	2.38	1.86	0.98	1.86	1.94
$(\times 10^6)$	(8.53)	(7.16)	(6.54)	(8.82)	(8.60)	(6.85)	(13.65)	(4.71)	(4.85)	(4.43)	(4.85)	(7.44)	(4.85)	(11.17)
γ_{ROA}	−0.52						−0.40	−0.18						−0.11
	(−2.62)						(−2.63)	(−1.31)						(−1.50)
γ_{MTB}		0.23					0.15		−0.07					0.24
$(\times 10^2)$		(5.53)					(3.75)		(−2.98)					(10.85)
γ_{RND}			0.53				−0.35			1.06				0.13
$(\times 10^2)$			(0.93)				(−0.98)			(1.84)				(0.71)
γ_{GIP}				−0.13			−0.06				−0.07			−0.04
$(\times 10^2)$				(−2.67)			(−1.78)				(−2.98)			(−2.44)
γ_{DEF}					1.10		1.29					0.34		0.54
$(\times 10^2)$					(8.63)		(12.50)					(8.93)		(10.54)
γ_{TMV}						0.59	0.42						0.00	0.36
						(10.88)	(4.19)						(−2.98)	(3.82)
$\bar{R}^2$(%)	38.36	43.51	37.38	37.05	56.38	35.47	72.88	19.62	20.04	24.74	20.04	41.84	20.04	80.57
Aggregate average idiosyncratic volatility computed from Fama–French 3-factor model														
δ	4.80	4.04	5.28	5.12	2.39	2.39	6.19	1.72	9.72	2.37	1.89	0.94	0.89	1.94
$(\times 10^6)$	(8.68)	(7.30)	(6.67)	(8.95)	(8.65)	(8.65)	(13.69)	(4.81)	(3.55)	(4.59)	(4.80)	(7.41)	(6.87)	(11.28)
γ_{ROA}	−0.53						−0.41	−0.20						−0.12
	(−2.71)						(−2.68)	(−1.48)						(−1.76)
γ_{MTB}		0.23					0.15		0.19					0.23
$(\times 10^2)$		(5.53)					(3.67)		(7.09)					(11.72)
γ_{RND}			0.49				−0.38			0.98				0.10
$(\times 10^2)$			(0.86)				(−1.06)			(1.81)				(0.56)
γ_{GIP}				−0.13			−0.06				−0.07			−0.04
$(\times 10^2)$				(−2.66)			(−1.87)				(−2.88)			(−2.52)
γ_{DEF}					1.09		1.28					0.34		0.51
$(\times 10^2)$					(8.55)		(12.26)					(8.74)		(10.60)
γ_{TMV}						0.01	0.39						0.23	0.33
						(8.55)	(4.16)						(7.09)	(4.12)
$\bar{R}^2$(%)	39.49	44.21	38.49	38.04	56.23	56.23	73.01	21.32	43.91	26.39	19.45	42.24	37.94	81.34
Aggregate average unconditional standard deviation														
δ	4.24	3.27	4.45	4.55	3.44	3.51	5.71	1.53	0.52	1.92	1.65	1.19	1.33	1.89
$(\times 10^6)$	(6.56)	(5.12)	(4.76)	(7.03)	(11.29)	(17.26)	(11.85)	(3.02)	(1.14)	(2.58)	(3.21)	(5.17)	(8.82)	(6.79)
γ_{ROA}	−0.51						−0.33	−0.18						−0.04
	(−2.03)						(−1.97)	(−0.93)						(−0.35)
γ_{MTB}		0.27					0.17		0.25					0.28
$(\times 10^2)$		(5.68)					(4.32)		(7.44)					(10.12)
γ_{RND}			0.99				−0.07			1.56				0.33
$(\times 10^2)$			(1.57)				(−0.19)			(2.30)				(1.40)
γ_{GIP}				−0.15			−0.06				−0.10			−0.05
$(\times 10^2)$				(−2.37)			(−1.85)				(−2.24)			(−1.88)
γ_{DEF}					0.29		1.60					0.39		0.95
$(\times 10^2)$					(0.86)		(11.38)					(2.19)		(8.58)
γ_{TMV}						0.83	0.63						0.87	0.71
						(4.86)	(5.28)						(7.76)	(5.32)
$\bar{R}^2$(%)	26.01	33.29	22.86	25.52	54.03	60.67	71.21	7.36	24.72	9.82	8.36	30.55	48.60	74.22

This table reports the estimation results of the interaction regression with the control variables. ROA is return on assets, MTB is the value-weighted firm level market value of assets over the book value of assets, RND is the value-weighted average of the scaled R&D expenditures, GIP is the growth rate in industrial production, DEF is the yield spread between BAA and AAA corporate bonds, and TMV is the realized variance of the value-weighted market index returns. The sample period for estimations is 1972.01–2014.12 for ROA and MTB, 1988.12–2014.12 for RND, 1972.02–2014.12 for GIP, and 1945.01–2014.12 for DEF and TMV. The Newey and West (1987) adjusted t-statistics under the Bartlett kernel with the Newey–West fixed bandwidth are presented in parentheses below the coefficient estimate. $\bar{R}^2$(%) is the adjusted R^2 in percentage.

Table 5
Trend regression on aggregate average volatility and residual volatility from interaction regression.

	Equal-weighted aggregate average idiosyncratic volatility						Value-weighted aggregate average idiosyncratic volatility					
	1945.01–2014.12		1945.01–2000.04		2000.05–2014.12		1945.01–2014.12		1945.01–2000.04		2000.05–2014.12	
	IVOL	RVOL	IVOL	RVOL	IVOL	RVOL	IVOL	RVOL	IVOL	RVOL	IVOL	RVOL
Aggregate average idiosyncratic volatility computed from the simple CAPM model												
$\lambda(\times 10^5)$	2.71	0.14	4.38	0.28	−10.70	1.08	0.88	−0.02	1.45	0.10	−6.31	1.08
	(8.40)	(0.66)	(18.03)	(1.14)	(−5.22)	(0.68)	(5.50)	(−0.12)	(9.21)	(0.60)	(−4.44)	(1.07)
$\overline{R}^2(\%)$	41.97	0.19	76.05	0.93	24.82	−0.18	21.39	−0.11	47.80	0.24	27.30	0.82
Aggregate average idiosyncratic volatility computed from the augmented CAPM model												
$\lambda(\times 10^5)$	2.69	0.14	4.36	0.28	−10.60	1.04	0.87	−0.01	1.43	0.10	−6.18	1.05
	(8.44)	(0.65)	(18.19)	(1.15)	(−5.28)	(0.67)	(5.58)	(−0.09)	(9.35)	(0.62)	(−4.42)	(1.06)
$\overline{R}^2(\%)$	42.35	0.18	76.75	0.98	25.33	−0.19	22.12	−0.11	49.48	0.28	27.37	0.82
Aggregate average idiosyncratic volatility computed from Fama–French 3-factor model												
$\lambda(\times 10^5)$	2.66	0.12	4.36	0.28	−10.70	1.02	0.82	−0.03	1.38	0.10	−6.19	1.02
	(8.35)	(0.55)	(18.23)	(1.16)	(−5.36)	(0.67)	(5.42)	(−0.26)	(9.50)	(0.63)	(−4.55)	(1.07)
$\overline{R}^2(\%)$	41.82	0.10	76.92	0.99	26.30	−0.19	21.43	−0.07	50.62	0.29	29.45	0.90
Aggregate average unconditional standard deviation												
$\lambda(\times 10^5)$	2.81	0.31	4.16	0.24	−9.68	1.11	1.15	0.14	1.50	0.49	−6.45	1.16
	(8.34)	(1.18)	(15.14)	(0.89)	(−4.27)	(0.57)	(5.52)	(0.75)	(7.40)	(0.24)	(−3.69)	(0.81)
$\overline{R}^2(\%)$	40.81	0.94	68.80	0.51	15.39	−0.31	19.21	0.27	31.02	−0.10	13.09	−0.01

This table reports the estimation results of the trend regressions. The estimated values of trend coefficients for aggregate idiosyncratic volatility are reported under Column IVOL, while Column RVOL reports the estimated values of trend coefficients for the residual volatility estimated from the interaction regression of Eq. (14). The Newey and West (1987) adjusted *t*-statistics under the Bartlett kernel with the Newey–West fixed bandwidth are presented in parentheses below the coefficient estimate. Note that Bunzel and Vogelsang's (2005) 5% asymptotic critical value is 2.05 for the statistical significance of the trend parameter. $\overline{R}^2(\%)$ is the adjusted R^2 in percentage.

difference between the nominal daily market portfolio return and the daily risk-free rate. We then use the root mean-squared error (RMSE) from each firm's monthly regression as the measure of individual monthly idiosyncratic volatility. We also use the monthly unconditional standard deviation of each stock as the fourth measure of volatility. We employ a simple average and market-capitalization weighted average of the RMSEs as the equal- and value-weighted aggregate idiosyncratic volatility.[4]

Plots (a) and (b) of Fig. 2 present the monthly equal- and value-weighted aggregate average idiosyncratic volatility computed from the Fama–French three factor model from 1926.07 to 2014.12. The plots indicate that aggregate idiosyncratic volatility increased dramatically in the late 1920s and then declined, with a local peak in 1932, until the mid-1940s. After this period, aggregate idiosyncratic volatility exhibits a persistent increase to the late 1990s and then sharply declines from the peak until 2014 with another significant local peak in 2008.

3.2. The effect of price interaction on aggregate idiosyncratic volatility

To test our price interaction hypothesis, we run the following interaction regression:

$$\sigma_{IV,t} = \mu + \delta N_t + \xi_t, \tag{14}$$

where N_t is the number of listed firms representing price interaction. The interaction parameter δ measures the effect of price interaction on aggregate idiosyncratic volatility. The positive value of δ implies that as more (less) firms are listed in the markets, aggregate idiosyncratic volatility increases (decreases). $\sigma_{IV,t}$ is the RMSEs estimated from the three capital asset pricing models and the aggregate average unconditional standard deviation. We select four different sample periods for the estimations of the interaction regression: 1926.07–2014.12, 1945.01–2014.12, 1945.01–2000.04, and 2000.05–2014.12. We choose 1945.01 as the beginning of the positive trend in aggregate idiosyncratic volatility to reflect the fact that the economic and financial systems during this Post-World War II period were different from those during the Pre-World War II period.[5] In addition, following Brandt et al. (2010), we choose 2000.04 as the end of the positive trend and 2000.05 as the beginning of a negative trend in aggregate idiosyncratic volatility.

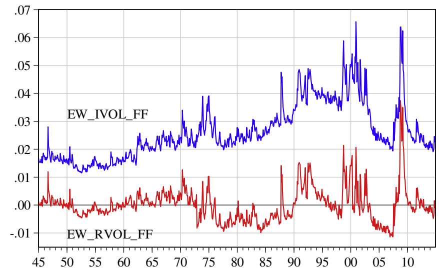
The estimation results are reported in Table 1 with the Newey and West (1987) adjusted t-statistics. The results show evidence to support the significant effect of price interaction on aggregate idiosyncratic volatility. For all four volatility measures, the estimated values of δ are all positive and statistically significant at the 5% level for all sample periods. The significant positive value of δ implies that as more (less) stocks are listed in the markets, stocks become more (less) volatile due to an increase (decrease) in the level of price co-movements resulting from price interaction among stocks. Another notable finding is that all of the interaction regressions yield a non-trivial level of adjusted R^2s. The average adjusted R^2 is 41.3% for the equal-weighted volatility and 27.7% for the value-weighted volatility. This indicates that price interaction is an important determinant of time variation in aggregate idiosyncratic volatility.

3.3. Robustness check of price interaction to other explanatory variables

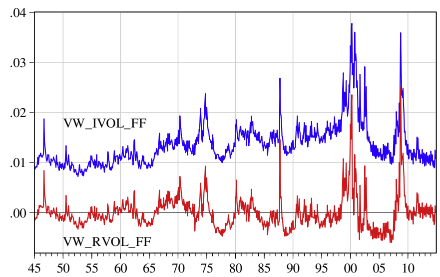
Many other explanatory variables have been suggested to account for the observed trend(s) and time variation in aggregate idiosyncratic volatility. In this section, we demonstrate that the effect of price interaction is mutually independent of the other explanatory variables that have been known to induce time variation and trend patterns of aggregate idiosyncratic volatility. To this end, we perform several robustness

[4] Market capitalizations at the end of the previous month are used to obtain the individual stock's weight. To obtain the number of listed firms, each month we count the listed firms included in computing the aggregate average idiosyncratic volatility.

[5] Brown and Kapadia (2007) show that many firms have become publicly traded in the post-war period increasing idiosyncratic volatility.



(a) The Level of Equal-Weighted Aggregate Idiosyncratic Volatilityand Residual Volatility



(b) The Level of Value-Weighted Aggregate Idiosyncratic Volatility and Residual Volatility

Fig. 3. Monthly aggregate idiosyncratic volatility and residual volatility (a) The level of equal-weighted aggregate idiosyncratic volatility and residual volatility (a) The level of value-weighted aggregate idiosyncratic volatility and residual volatility.

checks on the significance of our price interaction effect by running the following interaction regressions with the other explanatory variables augmented as the control variables:

$$\sigma_t = \mu + \delta N_t + \gamma CV_t + \omega_t, \tag{15}$$

where γ captures the effect of each control variable on aggregate idiosyncratic volatility.

The first control variable that we consider is the liquidity effect. A great deal of literature has confirmed that liquidity and idiosyncratic volatility are both important pricing factors in explaining expected stock returns.[6] Spiegel and Wang (2005) find that, while expected stock returns have a positive relation with idiosyncratic volatility, liquidity has a negative relation with expected stock returns. They also determine that, while playing a major role in determining stock returns, liquidity and idiosyncratic volatility are indeed inversely related with each other. Thus, we verify whether the price interaction effect is still robust to this important inverse relationship between liquidity and idiosyncratic volatility. Using Amihud's (2002) illiquidity measure, we first run a simple regression (LQ1) on liquidity alone and then run an interaction regression (LQ2) with liquidity augmented as the control variable. The estimation results are presented in Table 2. The results of the simple regression of liquidity shown under LQ1 indicate that for most of the regressions, the estimated values of the liquidity parameter (γ) are positive and statistically significant at the 5%. The positive value of γ indicates a negative relationship between aggregate idiosyncratic volatility and liquidity. Thus, our results are consistent with those reported by Spiegel and Wang (2005). The estimation results of the interaction regression reported under LQ2 provide strong evidence to support the positive interaction effect. For all four measures of volatility, the estimated values of the interaction coefficient (γ) under LQ2 are all positive and statistically significant at the 5% level, implying that the positive effect of price interaction on aggregate idiosyncratic volatility is still robust to the presence of the interaction between liquidity and idiosyncratic volatility.

The second control variable that we consider is the effect of newly listed firms in the markets. Brown and Kapadia (2007) find that many firms have become publicly traded in the post-war period and these firms are inherently riskier than existing public firms. As such, the newly listed firms exhibit persistently higher idiosyncratic volatility than the older firms.[7] They show that the newly listed firms exhibit persistently higher idiosyncratic volatility than the older firms, such that after controlling for the year that a firm lists, there is in general no significant trend in aggregate idiosyncratic volatility.

If the positive trend is attributed to the inclusion of newly listed firms, then the inclusion of new firms in the markets should explain the time variation in aggregate idiosyncratic volatility. To examine this possibility, we calculate the monthly change in the number of newly listed firms as $\Delta N_t = N_t - N_{t-1}$ and then run the simple regression of aggregate idiosyncratic volatility on ΔN_t for the two sample periods, 1926.07–2014.12 and 1945.01–2014.12. The results are reported under NFL1 in Table 3. None of the regressions show a statistically significant value of γ at the 5% level, indicating that the change in the number of newly listed firms cannot explain the variation of aggregate idiosyncratic volatility.

In addition, we manipulate the data of ΔN_t for the two sub-periods, such that all of the negative observations of ΔN_t for the sample period 1945.01–2000.04 are changed to zero, while all of the positive observations of ΔN_t are treated as zero for the sample period 2000.05–2014.12. The reason for this treatment in ΔN_t is that for the sample period 1945.01–2000.04 that exhibits a positive trend, we examine whether the inclusion of new firms can explain the observed positive trend for the period. For the sample period 2000.05–2014.12 that reports a negative trend, we examine whether the reduction in the number of listed firms can explain the sharp downturn for the period. The estimation results for 1945.01–2000.04 reported under NFL1 in Table 3 provide no evidence that the inclusion of the newly listed firms explains the variation of aggregate idiosyncratic volatility. However, the results for the 2000.05–2014.12 period show a significant effect of reduction in the number of listed firms. The estimated values of γ are all negative and statistically significant at the 5% level. Note that ΔN_t for the 2000.05–2014.12 period are all non-negative representing a monthly reduction in the number of firms. Thus, the negative sign of γ indicates that the reduction in the number of listed firms decreases aggregate idiosyncratic volatility, supporting the positive effect of price interaction on aggregate idiosyncratic volatility.

To determine the robustness of the price interaction effect under the effect of the newly listed firms, we run the interaction regression using ΔN_t as the control variable. The results are presented under NLF2 in Table 3 and also show strong evidence to support the positive price interaction effect. All the estimation results indicate that the estimated values of the interaction parameter (δ) are significantly positive at the 5% level for all four sample periods, implying that the significant positive effect of price interaction on idiosyncratic volatility is still robust to the presence of the effect of newly listed firms.

Bekaert, Hodrick, and Zhang (2012) examine the relative importance of the existing explanatory variables that have been proposed in the literature. They find that the cash flow variables, the business cycle variables, and market volatility are the most important determinants of the time variation in U.S. aggregate average idiosyncratic volatility. Thus, we examine whether the price interaction effect is still significant even in the presence of their explanatory variables. We use

[6] See Bali, Peng, Shen, and Tang (2014), Fu (2009), Hasbrouck (2009), Guo and Savickas (2008), Ang et al. (2006), Baker and Wurgler (2006), Bali et al. (2005), Ghysels, Santa-Clara, and Valkanov (2005), Acharya and Pedersen (2004), Baker and Stein (2004), Pástor and Stambaugh (2003), Goyal and Santa-Clara (2003), Amihud (2002), and Xu and Malkiel (2003).

[7] Fama and French (2004) also find that the newly listed firms in the 1980s and 1990s are characterized by more left-skewed in their profitability, more right-skewed in their growth, and lower survival rates.

Table 6
Interaction regression on detrended series of idiosyncratic volatility and number of listed firms with control variables.

	Equal-weighted aggregate average idiosyncratic volatility									Value-weighted aggregate average idiosyncratic volatility								
	DT	AMH	ROA	MTB	RND	GIP	DEF	TMV	Joint	DT	AMH	ROA	MTB	RND	GIP	DEF	TMV	Joint
Aggregate average idiosyncratic volatility computed from Fama–French 3-factor model																		
δ	3.44	2.57	3.51	3.71	4.99	3.73	3.40	3.34	3.34	1.31	1.19	1.36	1.45	1.88	1.45	1.25	1.24	1.33
$(\times 10^6)$	(8.41)	(5.68)	(7.71)	(8.00)	(9.29)	(8.54)	(7.56)	(8.59)	(11.60)	(6.18)	(4.37)	(6.36)	(6.69)	(5.68)	(6.98)	(5.70)	(6.54)	(7.86)
γ_{AMH}		6.40							12.53		0.88							2.01
		(4.69)							(11.92)		(1.12)							(3.05)
γ_{ROA}			−0.60						−0.13			−0.21						−0.07
			(−3.17)						(−1.21)			(−1.58)						(−1.21)
γ_{MTB}				0.23					0.26				0.19					0.25
$(\times 10^2)$				(6.10)					(6.16)				(7.63)					(11.27)
γ_{RND}					0.68				0.30					1.00				0.21
$(\times 10^2)$					(1.17)				(0.96)					(1.74)				(1.12)
γ_{GIP}						−0.12			−0.02						−0.07			−0.04
$(\times 10^2)$						(−2.65)			(−1.07)						(−3.16)			(−2.22)
γ_{DEF}							0.10		0.83							0.16		0.43
$(\times 10^2)$							(0.43)		(7.54)							(1.97)		(8.49)
γ_{TMV}								0.51	0.29								0.39	0.31
								(3.75)	(3.14)								(4.92)	(3.97)
$\bar{R}^2$(%)	38.84	45.82	41.00	46.37	53.79	38.39	36.11	41.62	89.18	20.78	24.52	47.54	29.85	24.30	23.93	34.07	83.69	83.69
Aggregate average unconditional standard deviation																		
δ	2.92	1.92	2.93	3.13	4.42	3.15	2.84	2.77	3.07	1.14	0.81	1.15	1.23	1.64	1.24	1.02	0.98	1.34
$(\times 10^6)$	(6.03)	(3.47)	(5.08)	(5.33)	(6.75)	(5.72)	(5.34)	(6.31)	(8.59)	(3.36)	(1.91)	(2.93)	(3.06)	(3.26)	(3.26)	(2.93)	(3.64)	(4.51)
γ_{AMH}		7.43							12.31		2.46							2.32
		(4.79)							(10.27)		(2.17)							(2.16)
γ_{ROA}			−0.59						−0.07			−0.21						0.00
			(−2.57)						(−0.52)			(−1.09)						(0.01)
γ_{MTB}				0.24					0.28				0.21					0.31
$(\times 10^2)$				(6.10)					(6.31)				(6.32)					(9.47)
γ_{RND}					1.07				0.52					1.47				0.40
$(\times 10^2)$					(1.66)				(1.46)					(2.11)				(1.63)
γ_{GIP}						−0.14			−0.03						−0.09			−0.05
$(\times 10^2)$						(−2.37)			(−1.02)						(−2.24)			(−1.66)
γ_{DEF}							0.22		1.16							0.33		0.86
$(\times 10^2)$							(0.74)		(7.18)							(2.07)		(7.00)
γ_{TMV}								0.83	0.53								0.87	0.70
								(5.21)	(4.48)								(8.07)	(5.13)
$\bar{R}^2$(%)	22.30	33.87	26.66	32.56	37.52	24.91	23.55	35.58	84.88	6.94	8.05	22.26	11.46	8.74	13.18	37.10	75.40	75.40

This table reports the estimation results of the interaction regression on the detrended idiosyncratic volatility and the detrended series of the number of listed firms with the control variables. DT indicates the estimation results of the simple interaction regression on the detrended idiosyncratic volatility with no control variables attached. AMH is the Amihud's (2002) illiquidity measure. ROA is the return on assets, MTB is the value-weighted firm level market value of assets over the book value of assets, RND is the value-weighted average of the scaled R&D expenditures, GIP is the growth rate in industrial production, DEF is the yield spread between BAA and AAA corporate bonds, and TMV is the realized variance of the value-weighted market returns. The Newey and West (1987) adjusted *t*-statistics are presented in parentheses below the coefficient estimate. $\bar{R}^2$(%) is the adjusted R^2 in percentage.

three cash flow variables: (a) return on assets (ROA)[8] as a proxy for the market power of the firms, (b) the value-weighted firm level market value of assets over the book value of assets (MTB) as a proxy for the growth option variable, and (c) the value-weighted average of firm level R&D expenditures scaled by sales (RND).[9] Following Bekaert et al. (2012), we use growth in industrial production (GIP) and default spread (DEF)[10] as the business cycle variables. GIP is computed as industrial production minus its own two year moving average, and DEF as the yield spread between BAA and AAA corporate bonds in the U.S. markets. The total market variance (TMV) is computed as the realized variance of the value-weighted market index returns. To check the robustness, we run the interaction regression with these variables augmented as both an individual control variable and the joint control variables. The results are reported in Table 4, which shows that for 55 of a total of 56 regressions, the estimated values of the interaction parameter (δ) are all positive and statistically significant at the 1% level. All eight regressions for the joint control variables still yield a significant positive value of δ at the 1% level, which is strong evidence to support the significant positive effect of price interaction on aggregate idiosyncratic volatility.

In sum, the results of the robustness checks show that the positive effect of price interaction on aggregate idiosyncratic volatility is still significant even under the presence of the other explanatory variables that are known as important in explaining aggregate idiosyncratic volatility. This implies that price interaction, as mutually independent of the other explanatory variables, is also an important determinant of aggregate idiosyncratic volatility.

3.4. Time trend under price interaction

In this section, we show that the observed trend in aggregate idiosyncratic volatility is attributed to the positive effect of price interaction on return volatility. We first identify the trend in aggregate idiosyncratic volatility by running the following linear time trend regression:

$$\sigma_{IV,t} = \mu + \lambda t + e_t, \tag{16}$$

where *t* is the time variable, and the trend coefficient (λ) captures a deterministic time trend, if any, in aggregate idiosyncratic volatility. We

[8] Following Irvine and Pontiff (2009), we compute ROA by summing a firm's earnings (Compustat Data Item 8) and interest payments (Item 22) over the past four quarters and dividing the result by last quarter's assets (Item 44). Note that since the Compustat data required to compute ROA is not widely available before 1972, our computed ROA data begins in January 1972.

[9] For the importance of MTB on idiosyncratic volatility, see Cao et al. (2008). To compute RND, we follow the method of Comin and Mulani (2006). For each firm, we compute its fiscal year R&D expenditure divided by the quarter's total revenue, and then construct the value-weighted average of the scaled R&D expenditures. For details, see Chun, Kim, Morck, and Yeung (2008) and Comin and Philippon (2005).

[10] For the importance of DEF in explaining economic activities, see Harvey (1988), Mueller (2009), and Gilchrist, Yankov, and Zakrajsek (2009).

Table 7
Interaction regression on Dow stocks.

	1945.01–2014.12				1945.01–2000.04				2000.05–2014.12			
	IV1	IV2	IV3	USD	IV1	IV2	IV3	USD	IV1	IV2	IV3	USD
AA($\times 10^6$)	0.98	0.93	0.89	1.05	0.80	0.76	0.73	0.79	3.52	3.15	3.36	1.83
	(5.64)	(5.64)	(5.44)	(5.24)	(5.45)	(5.40)	(5.14)	(4.72)	(3.06)	(2.90)	(3.27)	(2.10)
BA($\times 10^6$)	−0.06	−0.03	−0.05	−0.03	−0.07	−0.03	−0.06	−0.07	4.00	3.87	3.97	3.36
	(−0.33)	(−0.17)	(−0.28)	(−0.14)	(−0.36)	(−0.18)	(−0.31)	(−0.32)	(7.15)	(6.24)	(7.18)	(4.03)
CAT($\times 10^6$)	0.92	0.87	0.88	1.08	0.89	0.85	0.84	0.95	3.21	3.06	3.06	1.83
	(5.37)	(5.01)	(5.41)	(6.20)	(5.02)	(4.69)	(5.02)	(5.17)	(6.25)	(5.65)	(6.96)	(2.10)
DD($\times 10^6$)	1.17	1.18	1.13	1.34	1.12	1.14	1.08	1.23	3.78	3.57	3.59	2.48
	(8.30)	(8.30)	(9.17)	(8.70)	(7.90)	(7.92)	(8.81)	(7.85)	(4.92)	(4.87)	(4.97)	(2.74)
DIS($\times 10^6$)	−0.64	−0.58	−0.53	−0.40	−0.87	−0.79	−0.76	−0.63	5.18	4.87	5.29	4.89
	(−2.30)	(−2.06)	(−2.20)	(−2.35)	(−3.63)	(−3.21)	(−3.24)	(−2.35)	(7.43)	(6.47)	(7.49)	(4.58)
GE($\times 10^6$)	0.48	0.46	0.43	0.83	0.37	0.34	0.31	0.63	2.65	2.73	2.55	3.24
	(4.63)	(4.40)	(4.34)	(5.01)	(4.19)	(3.92)	(3.86)	(4.20)	(4.42)	(4.44)	(4.43)	(2.94)
HWP($\times 10^6$)	0.51	0.53	0.54	0.90	0.25	0.26	0.28	0.53	4.57	4.69	4.62	6.56
	(2.79)	(2.87)	(2.93)	(2.35)	(0.92)	(1.45)	(1.52)	(2.60)	(3.66)	(3.78)	(3.61)	(4.37)
IBM($\times 10^6$)	0.89	0.88	0.83	1.21	0.80	0.78	0.71	1.07	4.73	4.58	4.82	5.69
	(5.44)	(5.29)	(4.85)	(6.85)	(5.18)	(4.88)	(4.37)	(6.69)	(4.57)	(4.53)	(4.61)	(5.32)
IP($\times 10^6$)	0.55	0.53	0.49	0.76	0.46	0.46	0.40	0.60	2.02	1.60	1.91	0.55
	(3.16)	(3.13)	(2.94)	(3.74)	(2.80)	(2.83)	(2.58)	(3.02)	(2.39)	(1.84)	(2.15)	(0.36)
JNJ($\times 10^6$)	0.05	0.06	−0.05	0.46	0.08	0.09	−0.02	0.55	3.68	3.68	3.64	3.06
	(0.31)	(0.37)	(−0.34)	(2.65)	(0.52)	(0.59)	(−0.14)	(3.24)	(10.13)	(9.63)	(10.68)	(5.70)
KO($\times 10^6$)	0.67	0.64	0.54	1.08	0.62	0.61	0.49	1.10	4.19	3.91	3.97	3.63
	(4.63)	(4.68)	(4.11)	(6.93)	(4.71)	(4.75)	(4.11)	(6.89)	(5.66)	(5.56)	(6.01)	(5.18)
MMM($\times 10^6$)	−0.03	−0.02	−0.09	0.19	−0.06	−0.05	−0.12	0.13	3.26	3.30	3.17	2.49
	(−0.24)	(−0.16)	(−0.65)	(1.89)	(−0.41)	(−0.35)	(−0.91)	(0.74)	(7.18)	(7.36)	(7.35)	(3.83)
MO($\times 10^6$)	0.68	0.68	0.62	0.92	0.54	0.55	0.49	0.85	6.44	6.52	6.12	5.87
	(3.73)	(3.65)	(3.49)	(4.95)	(3.27)	(3.23)	(2.97)	(4.79)	(7.65)	(7.52)	(7.18)	(6.78)
MRK($\times 10^6$)	0.03	0.01	−0.03	0.30	−0.11	−0.11	−0.18	0.19	3.40	2.99	3.43	2.92
	(0.26)	(0.11)	(−0.22)	(2.14)	(−0.85)	(−0.87)	(−1.48)	(2.09)	(7.72)	(5.77)	(7.72)	(4.48)
PFE($\times 10^6$)	0.08	0.03	−0.04	0.35	0.04	0.01	−0.07	0.33	4.44	3.98	4.19	3.96
	(0.48)	(0.23)	(−0.27)	(2.09)	(0.29)	(0.09)	(−0.49)	(2.00)	(7.68)	(7.45)	(6.13)	(5.59)
PG($\times 10^6$)	0.74	0.73	0.66	1.10	0.70	0.69	0.62	1.10	3.69	3.62	3.70	3.24
	(4.77)	(4.65)	(4.46)	(6.79)	(4.56)	(4.44)	(4.30)	(6.53)	(6.28)	(6.01)	(6.32)	(5.46)
UTX($\times 10^6$)	−0.20	−0.21	−0.21	−0.06	−0.21	−0.22	−0.21	−0.15	4.85	4.64	4.54	4.30
	(−1.32)	(−1.46)	(−1.46)	(−0.36)	(−1.50)	(−1.64)	(−1.57)	(−0.89)	(9.00)	(8.03)	(8.47)	(4.65)
XOM($\times 10^6$)	0.85	0.83	0.75	0.79	0.78	0.76	0.69	0.69	3.10	3.03	3.08	2.01
	(8.62)	(8.44)	(8.04)	(6.05)	(7.73)	(7.56)	(7.37)	(4.97)	(9.63)	(9.25)	(9.97)	(2.93)
EW($\times 10^6$)	0.51	0.50	0.45	0.75	0.44	0.44	0.39	0.65	3.93	3.77	3.83	3.44
	(4.13)	(4.14)	(3.91)	(5.33)	(3.88)	(3.89)	(3.65)	(4.74)	(7.74)	(7.43)	(7.80)	(5.24)

This table reports the estimation results of the interaction regression on the 18 selected Dow stocks and their equal-weighted portfolio from 1945.01 to 2014.12. They are Altria Group (AA), Boeing (BA), Caterpillar (CAT), Du Pont (DD), Walt Disney (DIS), General Electric (GE), Hewlett–Packard (HWP), International Business Machine (IBM), International Paper (IP), Johnson & Johnson (JNJ), Coca Cola (KO), 3 M (MMM), Altria Group (MO), Merck (MRK), Pfizer (PFE), Procter & Gamble (PG), United Technologies (UTX), Exxon Mobil (XOM), and the equal-weighted portfolio (EW). IV1, IV2, IV3, and USD refer to the three idiosyncratic volatility measures and the unconditional standard deviation. The Newey and West (1987) adjusted *t*-statistics are presented in parentheses below the coefficient estimate.

estimate this trend model for the three different sample periods: 1945.01–2014.12, 1945.01–2000.04, and 2000.05–2014.12.[11]

The estimation results of the trend regression for all four volatility measures are presented under IVOL in Table 5. For the sample period 1945.01–2014.12, the estimated values of the trend coefficient (λ) under IVOL are all positive and statistically significant at the 1% level for both the equal- and value-weighed volatility. The results under IVOL for the 1945.01–2000.04 period also demonstrate a statistically significant positive trend, but a negative trend for the 2000.05–2014.12 period at the 1% significance level. The results are consistent with the trends reported by Brandt et al. (2010). The magnitude of the negative trend for the 2000.05–2008.09 sample period is much greater than that of positive trend for the 1945.01–2000.04 sample period, indicating a sharp downturn. We also estimated the trend model with the AR(1) term that is proposed by Vogelsang (1998), $\sigma^2_{IV,t}=\mu+\lambda t+\varphi\sigma^2_{IV,t-1}+e_t$. All the estimations indicate similar results to those reported in Table 5.[12] We also run the trend regression on the number of listed firms and confirm the same positive trend for the 1945.01–2000.04 period and a negative trend for the 2000.05–2014.12 period as observed in the aggregate idiosyncratic volatility.[13]

It is an important fact that the significant positive (negative) trend in aggregate idiosyncratic volatility from 1945.01 to 2000.04 (2000.05 to 2014.12) coincides with the same significant increase (decrease) in the number of listed firms over these two periods. In fact, the annual average growth rate in the number of firms listed in the U.S. equity markets was 4.7% from 1945.01 to 1999.12 and −3.8% from 2000.01 to 2014.12. This implies that there is a link between the trends in idiosyncratic volatility and price interaction. To test this link, we examine whether the residual volatility (ξ_t) estimated from the interaction regression of Eq. (14) still exhibits any remaining trend in the following trend regression:

$$\xi_t = \mu + \lambda t + v_t, \tag{17}$$

where ξ_t is the residual volatility estimated from the interaction regression of Eq. (14).

The estimation results are presented under RVOL in Table 5 and show no remaining trend in the residual volatility. Of a total of 24 trend

[11] Note that our sample period of 1945.01–2014.12 for the trend regression is longer than the sample period (1962.07–2008.09) used by Brandt et al. (2010).

[12] The estimated values of λ are all significant at the 1% level for all of the sample periods. The only difference is that the estimated values of λ are relatively smaller in the estimations of Vogelsang's (1998) model. The estimation results are not reported in the paper for reasons of brevity, but are available upon request.

[13] The estimation results can be summarized as follows: the estimated value of λ is 6.86 (t-value: 12.55) with adj.R^2 of 61.15% from 1945.01 to 2014.12, 11.58 (t-value: 40.88) with adj.R^2 of 92.66% from 1945.01 to 2000.04, and −14.62 (t-value: 13.20) with adj.R^2 of 90.00% from 2000.05 to 2014.12.

Table 8
Interaction regression with control variables for the portfolio average idiosyncratic volatility of Dow Stocks.

	Average idiosyncratic volatility from the simple CAPM model								*Average idiosyncratic volatility from the augmented CAPM model*							
	AMH	ROA	MTB	RND	GIP	DEF	TMV	Joint	AMH	ROA	MTB	RND	GIP	DEF	TMV	Joint
δ	0.51	1.42	0.90	2.09	1.59	0.45	0.45	1.45	0.50	1.41	0.89	2.08	1.56	0.44	0.44	1.48
$(\times 10^6)$	(3.98)	(4.52)	(3.38)	(4.76)	(4.75)	(2.91)	(3.86)	(6.81)	(4.00)	(4.56)	(3.47)	(4.93)	(4.79)	(2.96)	(3.89)	(6.97)
γ_{AMH}	1.46							1.14	1.37							1.04
	(2.64)							(2.44)	(2.51)							(2.17)
γ_{ROA}		−0.28						−0.17		−0.27						−0.15
		(−2.51)						(−2.93)		(−2.47)						(−2.64)
γ_{MTB}			0.15					0.21			0.15					0.20
$(\times 10^2)$			(5.62)					(9.14)			(5.81)					(8.67)
γ_{RND}				0.67				−0.02				0.68				0.02
$(\times 10^2)$				(1.52)				(−0.13)				(1.61)				(0.11)
γ_{GIP}					−0.05			−0.02					−0.05			−0.02
$(\times 10^2)$					(−2.63)			(−1.43)					(−2.69)			(−1.32)
γ_{DEF}						0.08		0.42						0.08		0.40
$(\times 10^2)$						(1.04)		(7.76)						(0.98)		(7.73)
γ_{TMV}							0.37	0.20							0.34	0.21
							(9.22)	(2.90)							(6.84)	(3.04)
$\bar{R}^2(\%)$	12.44	21.93	35.06	26.03	18.78	10.38	24.02	76.51	12.47	22.45	36.12	27.12	19.49	10.46	22.48	76.13
	Average idiosyncratic volatility from Fama–French 3-factor model								*Average unconditional standard deviation*							
δ	0.46	1.33	0.85	2.00	1.49	0.39	0.41	1.43	0.75	1.12	0.68	1.50	1.27	0.51	0.62	1.52
$(\times 10^6)$	(3.77)	(4.41)	(3.34)	(4.85)	(4.71)	(2.72)	(3.66)	(7.00)	(5.11)	(2.75)	(1.99)	(2.62)	(3.13)	(2.84)	(5.50)	(4.11)
γ_{AMH}	1.41							1.08	2.59							1.16
	(2.67)							(2.45)	(3.43)							(1.65)
γ_{ROA}		−0.27						−0.15		−0.27						−0.09
		(−2.61)						(−2.65)		(−1.77)						(−0.94)
γ_{MTB}			0.14					0.19			0.13					0.18
$(\times 10^2)$			(6.12)					(9.58)			(4.34)					(6.55)
γ_{RND}				0.60				−0.03				0.90				0.08
$(\times 10^2)$				(1.49)				(−0.24)				(2.07)				(0.40)
γ_{GIP}					−0.05			−0.02					−0.07			−0.02
$(\times 10^2)$					(−2.89)			(−1.54)					(−1.98)			(−0.73)
γ_{DEF}						0.09		0.41						0.33		0.81
$(\times 10^2)$						(1.10)		(8.19)						(2.22)		(7.64)
γ_{TMV}							0.31	0.19							0.82	0.60
							(5.39)	(2.89)							(9.41)	(4.84)
$\bar{R}^2(\%)$	11.76	22.10	34.65	26.19	19.10	9.69	20.02	76.07	13.47	6.91	11.02	7.16	6.11	15.95	41.58	68.04

This table reports the estimation results of the interaction regression with the control variables for the average idiosyncratic volatility of the portfolio of 18 Dow Stocks. AMH is the Amihud's (2002) illiquidity measure. ROA is the return on assets, MTB is the value-weighted firm level market value of assets over the book value of assets, RND is the value-weighted average of the scaled R&D expenditures, GIP is the growth rate in industrial production, DEF is the yield spread between BAA and AAA corporate bonds, and TMV is the realized variance of the value-weighted market index returns. The Newey and West (1987) adjusted *t*-statistics are presented in parentheses below the coefficient estimate. $\bar{R}^2(\%)$ is the adjusted R^2 in percentage.

regressions on residual volatility, none of the regressions yields an economically or statistically significant estimated value of λ. The magnitude of the trend coefficient (λ) is negligible for all of the regressions and none of the *t*-values are statistically significant even at the 10% level. The estimation results also report a very low level of adjusted R^2s indicating that once the number of listed firms is taken into account, no trend remains in aggregate idiosyncratic volatility. This result can be confirmed by Fig. 3, which illustrates the plots of the aggregate idiosyncratic volatility computed from the Fama–French three factor model (IVOL_FF) and the residual volatility (RVOL_FF) for the equal- and value-weighted volatility, respectively. The plots indicate that while aggregate idiosyncratic volatility exhibits an apparent positive trend (a sharp negative trend) from 1945.01 to 2000.04 (from 2000.05 to 2014.12), the residual volatility exhibits no trend remaining for the same periods.[14] This implies that the positive and negative patterns of time variation in aggregate idiosyncratic volatility is merely a reflection of the positive price interaction effect on returns volatility over time.

We also examine the price interaction effect on the *detrended* series of aggregate idiosyncratic volatility and the number of listed firms. We run the following interaction regression on the detrended series of aggregate idiosyncratic volatility and the number of listed firms with the aforementioned explanatory variables as the control variables:

$$d\sigma_t = \mu + \delta \cdot dN_t + \gamma \cdot CV_t + \omega_t, \qquad (18)$$

where $d\sigma_t$ and dN_t are the detrended series of aggregate idiosyncratic volatility and the number of listed firms, respectively. CV_t is the control variable, for which we use ROA, MTB, RND, GIP, DEF, and TMV as both the individual variable and the joint control variables in the interaction regression.

The estimation results are reported in Table 6, which shows strong evidence to support the significant positive effect of price interaction on aggregate idiosyncratic volatility. For space reasons, we only present the results for the Fama–French 3-factor model and the unconditional standard deviation.[15] The results show that for 35 of 36 regressions, the estimated values of the interaction parameter (δ) are all positive and statistically significant at the 1% level. This significant positive effect of price interaction estimated from the detrended series is still robust to the presence of the various control variables. The results from the detrended series verify that the positive price interaction effect is an important determinant of aggregate idiosyncratic volatility, thereby supporting our hypothesis.

[14] Note that the residual volatility series is the combined series of ξ_t, which is separately estimated for the two sample periods, July 1963–April 2000 and May 2000–September 2008, respectively.

[15] The results for the other two volatility measures are almost the same as those reported in Table 6.

Table 9
Interaction regression on firm size portfolios.

	1945.01–2014.12				1945.01–2000.04				2000.05–2014.12			
	IV1	IV2	IV3	USD	IV1	IV2	IV3	USD	IV1	IV2	IV3	USD
FS1($\times 10^6$)	7.41	7.34	7.42	7.24	6.98	6.93	6.99	6.80	13.00	12.80	12.90	13.00
	(15.24)	(15.18)	(15.21)	(14.66)	(12.90)	(12.82)	(12.84)	(12.41)	(5.34)	(5.36)	(5.35)	(5.25)
$\overline{R}^2$(%)	53.87	54.02	54.02	52.01	61.65	61.56	61.60	59.83	21.93	22.02	22.00	21.36
FS2($\times 10^6$)	5.50	5.47	5.52	5.29	5.35	5.33	5.37	5.13	9.56	9.43	9.50	9.41
	(19.35)	(19.36)	(19.39)	(18.04)	(18.01)	(17.94)	(17.98)	(16.85)	(5.70)	(5.73)	(5.70)	(5.46)
$\overline{R}^2$(%)	61.15	61.48	61.54	57.73	71.10	71.19	71.25	68.11	23.59	23.77	23.78	21.78
FS3($\times 10^6$)	4.48	4.47	4.49	4.26	4.43	4.43	4.44	4.19	6.95	6.88	7.03	6.35
	(19.35)	(19.51)	(19.50)	(17.62)	(18.00)	(18.08)	(18.07)	(16.51)	(5.82)	(5.86)	(5.99)	(4.89)
$\overline{R}^2$(%)	61.92	62.62	62.62	56.60	70.71	71.17	71.17	66.25	21.86	22.31	22.93	16.54
FS4($\times 10^6$)	3.90	3.89	3.91	3.71	3.82	3.82	3.83	3.60	6.75	6.75	7.04	5.37
	(19.10)	(19.36)	(19.35)	(17.20)	(17.97)	(18.14)	(18.15)	(16.32)	(6.59)	(6.78)	(7.23)	(4.23)
$\overline{R}^2$(%)	62.13	63.10	63.33	53.89	70.45	71.22	71.33	64.75	26.39	27.59	29.72	13.16
FS5($\times 10^6$)	3.47	3.46	3.46	3.31	3.33	3.33	3.33	3.11	6.75	6.69	7.00	5.29
	(19.33)	(19.69)	(19.70)	(16.78)	(18.65)	(18.90)	(19.01)	(16.19)	(8.11)	(8.27)	(8.86)	(4.75)
$\overline{R}^2$(%)	62.81	63.80	64.76	50.38	71.29	72.20	72.47	63.36	31.63	32.30	36.90	12.86
FS6($\times 10^6$)	3.18	3.16	3.13	3.06	2.99	2.98	2.97	2.79	7.72	7.63	7.79	6.50
	(17.65)	(18.03)	(17.97)	(15.09)	(17.82)	(18.13)	(18.16)	(15.08)	(10.42)	(10.58)	(10.95)	(6.32)
$\overline{R}^2$(%)	61.99	63.22	63.83	48.28	69.91	71.17	71.37	60.18	44.77	45.64	49.28	21.07
FS7($\times 10^6$)	2.73	2.71	2.67	2.66	2.54	2.53	2.50	2.37	7.86	7.72	7.80	7.04
	(15.07)	(15.39)	(15.35)	(12.75)	(16.15)	(16.48)	(16.57)	(13.30)	(9.63)	(9.61)	(9.77)	(6.52)
$\overline{R}^2$(%)	58.20	59.53	60.06	43.80	67.59	69.21	69.56	55.34	49.10	49.40	52.47	26.33
FS8($\times 10^6$)	2.26	2.24	2.18	2.26	2.07	2.05	2.01	1.96	7.61	7.49	7.42	7.08
	(12.24)	(12.44)	(12.38)	(10.55)	(13.03)	(13.25)	(13.29)	(10.84)	(9.62)	(9.62)	(9.51)	(6.80)
$\overline{R}^2$(%)	50.91	52.12	52.44	36.76	59.81	61.41	61.75	46.95	51.60	52.13	53.90	27.57
FS9($\times 10^6$)	1.85	1.82	1.78	1.89	1.70	1.68	1.64	1.64	6.53	6.42	6.33	6.16
	(10.60)	(10.73)	(10.78)	(9.04)	(11.15)	(11.33)	(11.44)	(9.14)	(8.03)	(7.92)	(8.01)	(5.76)
$\overline{R}^2$(%)	45.38	46.40	46.78	30.57	54.29	55.82	56.48	39.66	47.36	47.76	48.60	22.86
FS10($\times 10^6$)	1.31	1.29	1.25	1.49	1.16	1.15	1.11	1.27	5.00	4.88	4.88	5.28
	(9.28)	(9.35)	(9.40)	(8.32)	(9.73)	(9.81)	(9.97)	(8.23)	(6.83)	(6.70)	(7.02)	(5.75)
$\overline{R}^2$(%)	37.91	38.63	39.60	25.15	45.88	47.01	48.52	32.01	42.75	42.72	45.64	21.58

This table reports the estimated value of the interaction parameter from the interaction regression for the 10 size decile portfolios. FS1 is the portfolio of the smallest size docile. IV1, IV2, IV3, and USD refer to the three idiosyncratic volatility measures and the unconditional standard deviation. The Newey and West (1987) adjusted *t*-statistics are presented in parentheses below the coefficient estimate. $\overline{R}^2$(%) is the adjusted R^2 in percentage.

4. Evidence of price interaction effect from individual stocks

Thus far, we test our hypothesis by using aggregate idiosyncratic volatility. In this section, we test our hypothesis for the individual stocks. Given that σ^2_{UV} and σ^2_{IV} are the simple average of the individual stock's unconditional variances and individual idiosyncratic variances, it is required that $\frac{\partial \sigma^2_i}{\partial N}>0$ and $\frac{\partial \sigma^2_{iv}}{\partial N}>0$ for individual volatility are consistent with $\frac{\partial \sigma^2_{UV}}{\partial N}>0$ and $\frac{\partial \sigma^2_{IV}}{\partial N}>0$ for aggregate volatility to support the price interaction hypothesis. We thus examine whether there still exists a positive effect of price interaction on individual stock volatility.

We use the Dow Jones stocks whose daily returns cover the sample period from 1945.01 to 2014.12. The purpose is to control the possible volatility effect of newly listed firms, as newly listed or young firms are expected to be relatively riskier than concurrently existing firms. Under this criterion, 18 individual Dow stocks are selected. They are Altria Group (AA), Boeing (BA), Caterpillar (CAT), Du Pont (DD), Walt Disney (DIS), General Electric (GE), Hewlett-Packard (HWP), International Business Machines (IBM), International Paper (IP), Johnson & Johnson (JNJ), Coca Cola (KO), 3 M (MMM), Altria Group (MO), Merck (MRK), Pfizer (PFE), Procter & Gamble (PG), United Technologies (UTX), and Exxon Mobil (XOM). We also form an equally-weight portfolio of these 18 Dow stocks, such that we generate a total of 19 time series for each volatility measure to run the interaction regression.

The estimation results of a total of 228 interaction regressions ($= 19 \times 4$ volatility measures $\times$ 3 sample periods) are presented in Table 7. IV1, IV2, and IV3 refer to the three portfolio average idiosyncratic volatility measures estimated from the simple CAPM, the augmented CAPM, and the Fama–French three factor model, respectively, and USD refers to the average unconditional standard deviation. Of 228 regressions, 173 (76%) interaction regressions report a statistically significant positive value of δ at the 5% level. For each sample period, we run a total of 76 regressions (19×4 volatility measures). Of these 76 regressions, the number of statistically significant positive values of δ is 51 (67%) from 1945.01 to 2014.12, 48 (63%) from 1945.01 to 2000.04, and 74 (97%) from 2000.05 to 2014.12. For each volatility measure, we run a total of 57 regressions for the three sample periods (19×3 sample periods). Of these 57 regressions, the number of statistically significant positive values of δ for each volatility measure is 43 (57%) for IV1, 44 (58%) for IV2, 42 (55%) for IV3, and 48 (63%) for USD. A significant positive value of δ implies that individual stocks become more (less) volatile as N increases (decreases). The results indicate that the positive effect of price interaction is still significant even for individual stock volatility.

We also check the robustness of the positive effect of price interaction to the aforementioned other explanatory variables. Using the four volatility measures of the equally-weighted portfolio of the 18 individual Dow stocks, we run the interaction regression of Eq. (15) with the other explanatory variables augmented as the control variable(s). The estimation results are reported in Table 8. There are two notable findings. First, most of individual control variables are statistically significant at the 5% level with the same signs as shown in the results for aggregate idiosyncratic volatility. This implies that the control variables have significant explanatory power to explain the time variation in idiosyncratic volatility of individual stocks. Second, the positive effect of price interaction is still significant even with the control variables.

5. Firm-size effect in price interaction

Several studies have found that idiosyncratic volatility is inversely related with the level of stock price. For example, Bennett et al. (2003)

Table 10
Interaction regression with control variables on firm size portfolios.

	FS1	FS2	FS3	FS4	FS5	FS6	FS7	FS8	FS9	FS10
Idiosyncratic volatility computed from Fama–French 3-factor model										
$\delta(\times 10^6)$	14.60	9.64	7.38	6.07	4.98	4.60	4.07	3.52	2.77	1.70
	(13.22)	(11.97)	(11.05)	(10.60)	(11.78)	(11.81)	(12.30)	(12.64)	(13.12)	(9.80)
γ_{ROA}	−0.88	−0.60	−0.46	−0.43	−0.40	−0.43	−0.33	−0.27	−0.16	−0.11
	(−2.55)	(−2.16)	(−2.08)	(−2.27)	(−2.65)	(−3.11)	(−2.44)	(−2.53)	(−2.05)	(−1.65)
$\gamma_{MTB}(\times 10^2)$	−0.03	0.02	0.03	0.07	0.12	0.17	0.23	0.27	0.29	0.24
	(−0.23)	(0.22)	(0.68)	(1.62)	(3.51)	(5.82)	(8.01)	(11.54)	(12.80)	(11.82)
$\gamma_{RND}(\times 10^2)$	1.09	−0.99	−1.29	−1.20	−0.96	−0.58	−0.37	−0.25	−0.10	0.09
	(1.00)	(−1.50)	(−2.16)	(−2.28)	(−2.47)	(−1.87)	(−1.46)	(−1.14)	(−0.55)	(0.58)
$\gamma_{GIP}(\times 10^2)$	−0.08	−0.09	−0.06	−0.06	−0.07	−0.06	−0.05	−0.04	−0.04	−0.04
	(−1.10)	(−1.63)	(−1.34)	(−1.58)	(−2.08)	(−1.83)	(−1.91)	(−1.79)	(−2.29)	(−2.55)
$\gamma_{DEF}(\times 10^2)$	2.66	1.97	1.58	1.33	1.10	0.93	0.80	0.75	0.68	0.49
	(8.28)	(10.78)	(11.30)	(10.53)	(9.14)	(8.22)	(7.33)	(8.11)	(9.87)	(10.16)
γ_{TMV}	0.49	0.51	0.37	0.40	0.36	0.33	0.37	0.37	0.35	0.33
	(2.64)	(3.86)	(3.35)	(3.41)	(3.84)	(3.96)	(4.25)	(4.67)	(4.18)	(4.21)
$\overline{R}^2(\%)$	61.11	65.75	64.24	65.46	68.69	71.97	75.33	80.26	82.88	81.34
Unconditional standard deviation										
$\delta(\times 10^6)$	14.50	9.49	6.97	5.28	4.19	3.83	3.34	2.94	2.38	1.74
	(13.08)	(11.86)	(10.37)	(8.91)	(8.99)	(8.87)	(8.83)	(8.40)	(7.44)	(6.30)
γ_{ROA}	−0.89	−0.61	−0.44	−0.29	−0.22	−0.29	−0.21	−0.19	−0.11	−0.03
	(−2.59)	(−2.18)	(−1.90)	(−1.40)	(−1.22)	(−1.88)	(−1.39)	(−1.39)	(−0.92)	(−0.26)
$\gamma_{MTB}(\times 10^2)$	−0.02	0.03	0.05	0.09	0.14	0.20	0.26	0.32	0.34	0.29
	(−0.14)	(0.39)	(0.98)	(1.96)	(3.87)	(6.65)	(8.44)	(10.88)	(10.98)	(10.25)
$\gamma_{RND}(\times 10^2)$	1.09	−0.96	−1.22	−0.84	−0.45	−0.08	0.13	0.23	0.23	0.31
	(1.01)	(−1.46)	(−1.99)	(−1.46)	(−1.08)	(−0.23)	(0.42)	(0.80)	(0.86)	(1.32)
$\gamma_{GIP}(\times 10^2)$	−0.09	−0.09	−0.06	−0.05	−0.06	−0.05	−0.06	−0.05	−0.05	−0.06
	(−1.22)	(−1.68)	(−1.30)	(−1.44)	(−2.00)	(−1.74)	(−1.82)	(−1.66)	(−1.73)	(−1.91)
$\gamma_{DEF}(\times 10^2)$	2.72	2.05	1.68	1.54	1.53	1.42	1.25	1.23	1.15	0.92
	(8.46)	(10.73)	(11.08)	(11.53)	(10.12)	(9.65)	(9.39)	(10.15)	(9.80)	(8.25)
γ_{TMV}	0.56	0.59	0.48	0.61	0.65	0.62	0.66	0.69	0.70	0.72
	(2.95)	(4.33)	(4.23)	(4.52)	(4.72)	(5.48)	(5.58)	(6.24)	(5.46)	(5.28)
$\overline{R}^2(\%)$	61.19	65.92	62.96	61.92	66.41	69.17	71.01	75.16	76.08	74.12

This table reports the estimation results of the interaction regression on the idiosyncratic volatility of 10 size decile portfolios with the six control variables. The Newey and West (1987) adjusted t-statistics are presented in parentheses below the coefficient estimate. $\overline{R}^2(\%)$ is the adjusted R^2 in percentage.

and Xu and Malkiel (2003) find that increased institutional ownership to hold low priced stocks is attributed to the trend in aggregate idiosyncratic volatility. Brandt et al. (2010) suggest that low priced stocks exhibit a relatively higher level of idiosyncratic volatility and a more evident volatility trend. They argue that low priced stocks held for speculation by retail investors play an important role in inducing the trend patterns observed in aggregate idiosyncratic volatility. Their argument has important empirical implications for the validity of our price interaction hypothesis. If the size effect in idiosyncratic volatility is associated with the trading activity of retail investors who trade low priced stocks speculatively, then the similar size effect should exist in the level of price interaction for low priced stocks such that low priced stocks should exhibit a relatively higher level of price interaction than others. Note that the rationale of the price interaction hypothesis is based on the fact that stocks covary with each other. The size effect, if any, in price interaction implies that low priced stocks are more likely to exhibit a greater level of price co-movements and hence a higher volatility. Thus, the coexistence of the size effect in price interaction and volatility is strong evidence to support our argument that price interaction is an important determinant of the time variation in idiosyncratic volatility.

We employ the idiosyncratic volatility of ten size decile portfolios from the NYSE, AMEX, and NASDAQ stocks. From the plots of idiosyncratic volatility of size portfolios, we find a significant size effect in both the idiosyncratic volatility and the time trends, which is similar to that demonstrated in Brandt et al. (2010). The level of volatility and the positive and negative volatility trends are more evident among small sized portfolios.[16] To examine the size effect in price interaction, we run the interaction regression on the idiosyncratic volatility of each size portfolio and compare the magnitude of the interaction coefficients. The estimation results are reported in Table 9. All of the 120 interaction regressions exhibit a statistically significant positive effect of price interaction on idiosyncratic volatility at the 1% level. In addition, there is a significant size effect in price interaction among size portfolios such that the estimated value of the interaction coefficients increases as size decreases. For all three sample periods, the Size Decile 1 Portfolio (FS1—the smallest decile) exhibits the greatest magnitude of the interaction parameter, while the Size Decile 10 Portfolio (FS10—the largest decile) exhibits the smallest magnitude. Moreover, the magnitude of the interaction parameter increases *monotonically* as the size decreases except for the 2000.05–2014.12 period.

We also check the robustness of the price interaction effect among size portfolios by running the interaction regression with the three cash

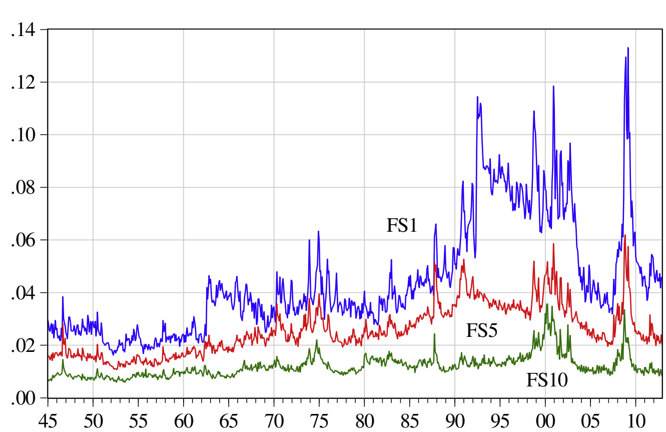


Fig. 4. The level of monthly idiosyncratic volatility of size decile portfolios.

[16] The plots are not reported in the paper for reasons of brevity, but they are available upon request.

Table 11
Trend regression on idiosyncratic volatility and residual volatility on firm size portfolios.

	Idiosyncratic volatility from Fama–French three-factor model						Unconditional standard deviation					
	1945.01–2014.12		1945.01–2000.04		2000.05–2014.12		1945.01–2014.12		1945.01–2000.04		2000.05–2014.12	
	IVOL	RVOL	IVOL	RVOL	IVOL	RVOL	IVOL	RVOL	IVOL	RVOL	IVOL	RVOL
FS1($\times 10^6$)	5.78	0.70	8.69	0.59	−18.10	0.81	5.64	0.67	8.42	0.55	−18.20	0.83
	(9.02)	(1.47)	(12.79)	(0.90)	(−4.65)	(0.22)	(8.71)	(1.38)	(12.04)	(0.81)	(−4.58)	(0.22)
$\overline{R}^2$(%)	42.56	1.22	65.74	0.65	18.05	−0.53	40.91	1.10	63.42	0.52	17.50	−0.53
FS2($\times 10^6$)	3.97	0.18	6.67	0.45	−12.80	1.08	3.80	0.17	6.35	0.41	−12.60	1.13
	(8.42)	(0.56)	(17.98)	(1.23)	(−4.54)	(0.45)	(7.99)	(0.49)	(16.03)	(1.07)	(−4.36)	(0.45)
$\overline{R}^2$(%)	41.05	0.10	76.04	1.08	18.07	−0.40	38.34	0.05	72.13	0.79	16.40	−0.40
FS3($\times 10^6$)	3.14	0.06	5.52	0.37	−9.24	1.04	3.03	0.11	5.19	0.33	−8.05	1.22
	(8.29)	(0.23)	(18.12)	(1.22)	(−4.40)	(0.60)	(8.03)	(0.41)	(15.74)	(1.04)	(−3.58)	(0.64)
$\overline{R}^2$(%)	39.49	−0.08	75.86	1.05	16.53	−0.29	37.11	−0.01	70.14	0.71	11.04	−0.25
FS4($\times 10^6$)	2.71	0.02	4.75	0.31	−9.41	0.89	2.78	0.23	4.45	0.28	−6.70	1.15
	(8.22)	(0.11)	(18.69)	(1.20)	(−5.14)	(0.62)	(8.49)	(0.92)	(15.99)	(1.02)	(−3.08)	(0.60)
$\overline{R}^2$(%)	39.07	−0.11	75.74	0.99	22.21	−0.29	39.00	0.46	68.37	0.62	8.42	−0.27
FS5($\times 10^6$)	2.43	0.06	4.10	0.25	−9.49	0.75	2.65	0.37	3.82	0.21	−6.92	0.81
	(8.52)	(0.32)	(18.70)	(1.12)	(−6.04)	(0.66)	(8.77)	(1.50)	(15.07)	(0.87)	(−3.63)	(0.47)
$\overline{R}^2$(%)	41.25	−0.05	75.96	0.83	28.43	−0.29	41.47	1.52	65.85	0.41	9.13	−0.42
FS6($\times 10^6$)	2.15	0.00	3.63	0.19	−10.50	0.85	2.44	0.34	3.38	0.15	−8.67	0.84
	(8.02)	(0.02)	(17.50)	(0.93)	(−6.52)	(0.79)	(8.47)	(1.43)	(13.72)	(0.64)	(−4.56)	(0.52)
$\overline{R}^2$(%)	38.81	−0.12	73.68	0.56	37.89	−0.08	39.59	1.35	61.08	0.15	15.63	−0.38
FS7($\times 10^6$)	1.80	−0.03	3.06	0.17	−10.20	1.24	2.12	0.29	2.87	0.12	−9.07	1.23
	(7.31)	(−0.22)	(15.77)	(0.85)	(−5.60)	(1.06)	(7.81)	(1.27)	(11.89)	(0.53)	(−4.38)	(0.74)
$\overline{R}^2$(%)	34.94	−0.09	72.05	0.54	37.37	0.62	35.63	1.05	56.00	0.08	18.22	−0.10
FS8($\times 10^6$)	1.42	−0.07	2.46	0.13	−9.63	1.21	1.79	0.24	2.36	0.09	−9.11	1.24
	(6.36)	(−0.46)	(12.39)	(0.64)	(−5.50)	(1.08)	(6.90)	(1.08)	(9.66)	(0.38)	(−4.45)	(0.76)
$\overline{R}^2$(%)	28.57	0.03	63.70	0.30	38.12	0.76	29.74	0.73	47.10	−0.02	19.06	−0.07
FS9($\times 10^6$)	1.14	−0.08	2.00	0.10	−8.03	1.22	1.46	0.17	1.95	0.05	−7.63	1.37
	(5.83)	(−0.53)	(10.62)	(0.51)	(−4.90)	(1.11)	(6.05)	(0.78)	(8.05)	(0.22)	(−3.78)	(0.84)
$\overline{R}^2$(%)	24.66	0.09	57.84	0.17	32.82	0.92	23.62	0.33	38.84	−0.10	14.61	0.06
FS10($\times 10^6$)	0.86	0.01	1.38	0.10	−6.11	1.02	1.18	0.15	1.52	0.05	−6.55	1.17
	(5.94)	(0.06)	(9.64)	(0.65)	(−4.50)	(1.08)	(5.78)	(0.83)	(7.67)	(0.27)	(−3.77)	(0.82)
$\overline{R}^2$(%)	24.35	−0.12	51.99	0.35	29.95	1.01	20.17	0.34	31.86	−0.09	13.77	0.02

This table reports the estimation results of the trend regressions on the idiosyncratic volatility and unconditional standard deviation of 10 size decile portfolios. Column IVOL reports the estimated values of trend coefficients for the idiosyncratic volatility, while Column RVOL reports the estimated values of trend coefficients for the residual volatility estimated from the interaction regression of Eq. (14). The Newey and West (1987) adjusted *t*-statistics are presented in parentheses below the coefficient estimate. Note that Bunzel and Vogelsang's (2005) 5% asymptotic critical value is 2.05 for the statistical significance of the trend parameter. $\overline{R}^2$(%) is the adjusted R^2 in percentage.

flow variables (ROA, MTB, and RND), the two business cycle variables (GIP and DEF), and the market volatility (TMV) together as the joint control variables. The estimation results are reported in Table 10, which shows a significant positive effect of price interaction for all size portfolios. For space reasons, we report only the results for the Fama–French three factor model and the unconditional standard deviation for each size portfolio. For all 20 regressions, the estimated values of the interaction parameter (δ) are still positive and statistically significant at the 1% level, even under the presence of all six control variables.

Brandt et al. (2010) find that low priced stocks exhibit a relatively more evident trend pattern in idiosyncratic volatility. We also observe the same trend pattern in the idiosyncratic volatility of the ten size decile portfolios. Fig. 4 illustrates that the trend pattern is more evident in the idiosyncratic volatility of FS1 than of FS5 and FS10. We now examine whether the observed trend pattern in idiosyncratic volatility of each size portfolio can be explained by the positive price interaction effect. We run the linear trend regression on the idiosyncratic volatility of each size portfolio to confirm the time trend. Then, we run the trend regression on the residual volatility of each size portfolio that is estimated from running the interaction regression of Eq. (14) on the idiosyncratic volatility of each size portfolio. We demonstrate that under the positive price interaction effect, there is no trend remaining in the residual volatility of each size portfolio.

The estimation results of the two trend regressions on idiosyncratic volatility and residual volatility, respectively, are presented in Table 11. For brevity, we report only the results for the Fama–French three factor model and the unconditional standard deviation for each size portfolio.[17] IVOL reports the trend estimates of the idiosyncratic volatility of each size portfolio, while RVOL provides the trend estimates of residual volatility. For all size portfolios, the estimated values of the trend coefficient (λ) under IVOL are positive and statistically significant at the 1% level for the period 1945.01–2014.12 and 1945.01–2000.04, while they are significantly negative for the 2000.05–2014.12 period at the 1% level. The results of the significant positive and negative trends are consistent with the results for aggregate idiosyncratic volatility. As expected, there is a size effect similar to the one that we observe from the estimation of the interaction regressions. The estimated value of the trend parameter increases as size decreases. For all three sample periods, the magnitude of the trend parameter is greatest for the Size Decile 1 Portfolio (FS1) and smallest for the Size Decile 10 Portfolio (FS10) and, with the exception of the 2000.05–2014.12 period, the magnitude increases monotonically as the size decreases.

The estimation results of the trend regression regarding the residual volatility of each size portfolio are presented under RVOL in Table 11. None of the regressions yield an economically or statistically significant estimated value of the trend coefficient. Similar to the results for aggregate idiosyncratic volatility, the magnitude of all of the trend coefficients are negligible for a total of 30 regressions with insignificant

[17] For the estimation results for the other two volatility measures are almost the same as those results reported in Table 11. They are available upon request.

t-values. Additionally, all 30 regressions yield a very low level of adjusted R^2s. The results are consistent with those results for aggregate idiosyncratic volatility in that once the effect of price interaction is taken into account, no trend remains in idiosyncratic volatility. The results for individual Dow stocks and size portfolios verify that the observed pattern of positive and negative trends in idiosyncratic volatility is attributed to the positive effect of price interaction on return volatility.

6. Summary and conclusion

In this paper, we hypothesize and demonstrate that as more (less) stocks are listed in the markets, the level of price interaction per stock increases (decreases), thereby increasing (decreasing) aggregate average idiosyncratic volatility. Our results indicate that there is a significant positive effect of price interaction on aggregate idiosyncratic volatility, and a substantial portion of the time variation in idiosyncratic volatility is explained by this positive price interaction effect. The results of various robustness checks indicate that the positive interaction effect is still significant to the presence of liquidity, newly listed firms, cash flow variables, business cycle variables, and market volatility.

We find that price interaction is attributed to the trend observed in aggregate idiosyncratic volatility. Our results show that once the effect of price interaction is taken into account, no trend remains in idiosyncratic volatility, implying that the observed trend in aggregate idiosyncratic volatility is merely a reflection of the positive price interaction effect on volatility. In fact, the significant positive (negative) trend from 1945.01 to 2000.04 (2000.05 to 2014.12) coincides with a significant increase (decrease) in the number of listed firms during the same period(s). This verifies that a steady increase in the number of firms listed in the markets from the 1945.01–2000.04 period caused stocks to be more volatile due to the increased price interactions among stocks inducing a positive trend in aggregate idiosyncratic volatility over this period. Likewise, the steep downturn observed from the 2000.05–2014.12 period is attributed to the sharp decline in the number of listed stocks during this period that dramatically reduced the level of price interaction among stocks decreasing the level of aggregate idiosyncratic volatility.

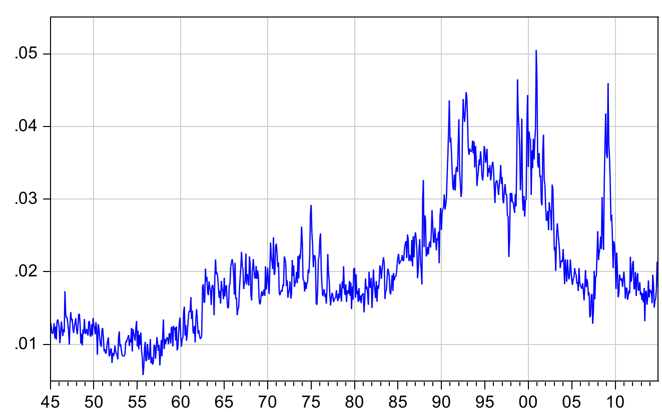
In addition, we show that there is the same size effect in both idiosyncratic volatility and price interaction among the size portfolios. Our results indicate that not only idiosyncratic volatility but also price interaction increases monotonically as the size decreases, indicating that low priced stocks are more likely to exhibit a greater level of price interaction and hence a higher volatility. The results support the role of price interaction as an important determinant of idiosyncratic volatility. Therefore, we conclude that price interaction is an important determinant of idiosyncratic volatility and there is no trend in aggregate idiosyncratic volatility.

Appendix A. Model-independent aggregate idiosyncratic volatility.

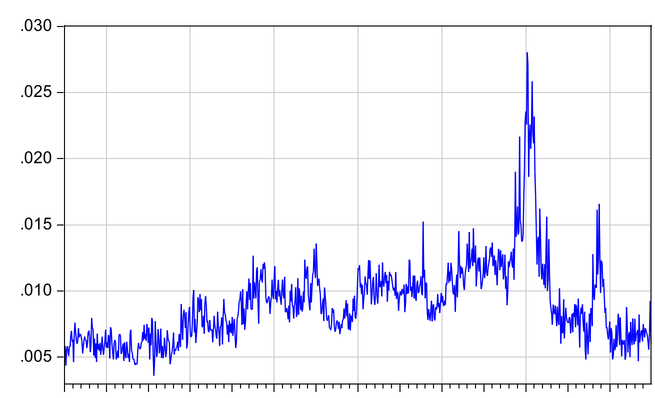
Utilizing the concept of gain from portfolio diversification, Bali, Cakici, and Levy (2008) propose a model-independent measure of aggregate idiosyncratic volatility, which does not require estimation of market betas or correlations. They define the new measure of aggregate average idiosyncratic volatility as the difference between the variance of the non-diversified portfolio and the variance of the fully diversified market portfolio. Using the method of Bali et al. (2008) that decomposes total risk into firm and market variance, we construct three model-independent aggregate idiosyncratic volatility over the 1945.01–2014.12 period for the NYSE/AMEX/NASDAQ (NYAXQ) stocks, the NYSE/AMEX (NYAX) stocks, and the NASDAQ (NASDQ) stocks. Appendix Fig. 1 shows the monthly model-independent aggregate idiosyncratic volatility over the 1945.01–2014.12 period for the NYSE/AMEX/NASDAQ (NYAXQ) stocks. The pattern of upward trend for the 1990s and downward trend for the (2000s) is consistent with those shown in the aggregate idiosyncratic volatility series in Fig. 1.

For both the equal- and value-weighted aggregate idiosyncratic volatility, we estimate interaction regression, trend regression, and joint-test regression for the three different sample periods, 1945.01–2014.12, 1945.01–2000.04, and 2000.05–2014.12. The estimation results are reported in Appendix Tables 1 & 2 with the Newey and West (1987) adjusted t-statistics. Notable findings are as follows:

1. The positive effect of price interaction is still significant for all three series of model-independent aggregate idiosyncratic volatility. The results confirm that price interaction is an important determinant of time variation in aggregate average idiosyncratic volatility.
2. All the model-independent aggregate idiosyncratic volatility series exhibit a significant positive trend for the 1945.01–2000.04 period and a negative trend for 2000.05–2014.12 sample period. The results are consistent with those reported in Table 6.
3. Once the price interaction effect is taken into account, no trend remains in the model-independent aggregate idiosyncratic volatility. This result implies that the observed trend is a reflection of the positive effect of price interaction on idiosyncratic risk, thereby supporting the price interaction hypothesis.
4. The results of the joint-test regression on the model-independent aggregate idiosyncratic volatility confirm that the positive effect of price interaction is still significant even under the presence of the other explanatory variables that are known as important in explaining aggregate idiosyncratic volatility. The results support that the effect of price interaction is a robust driving force of time variation in aggregate idiosyncratic volatility.



(a) Equal-Weighted Aggregate Idiosyncratic Volatility



(b) Value-Weighted Aggregate Idiosyncratic Volatility

Appendix Fig. 1. Monthly model-independent aggregate average idiosyncratic volatility.

Appendix Table 1 Interaction and trend regression on model-independent aggregate idiosyncratic volatility and residual volatility.

Panel 1. Interaction regression on model-independent aggregate idiosyncratic volatility

	1945.01–2014.12			1945.01–2000.04			2000.05–2014.12		
	NYAXQ	NYAX	NASDQ	NYAXQ	NYAX	NASDQ	NYAXQ	NYAX	NASDQ
Equal-weighted aggregate average idiosyncratic volatility									
$\delta(\times 10^6)$	3.09	1.06	6.42	3.00	1.01	8.29	6.09	1.92	7.12
	(17.28)	(7.49)	(10.57)	(15.92)	(6.93)	(11.84)	(7.67)	(4.04)	(7.71)
$\bar{R}^2$(%)	62.01	23.61	47.47	66.69	26.49	56.62	42.61	9.21	46.22
Value-weighted aggregate average idiosyncratic volatility									
$\delta(\times 10^6)$	0.95	0.47	3.50	0.90	0.50	2.83	4.00	2.15	6.27
	(9.50)	(7.65)	(8.36)	(10.97)	(8.22)	(6.87)	(6.24)	(6.69)	(5.90)
$\bar{R}^2$(%)	41.02	20.89	47.45	51.12	31.04	38.31	61.36	45.86	62.33

Panel 2. Trend regressions on model-independent aggregate idiosyncratic volatility

	Equal-weighted aggregate idiosyncratic volatility						Value-weighted aggregate idiosyncratic volatility					
	1945.01–2000.04			2000.05–2014.12			1945.01–2000.04			2000.05–2014.12		
	NYAXQ	NYAX	NASDQ	NYAXQ	NYAX	NASDQ	NYAXQ	NYAX	NASDQ	NYAXQ	NYAX	NASDQ
$\lambda(\times 10^5)$	3.79	1.30	8.98	−8.05	−2.50	−9.40	1.16	0.67	3.19	−4.91	−2.76	−7.62
	(16.73)	(8.68)	(14.11)	(−5.26)	(−3.11)	(−5.27)	(11.70)	(9.97)	(7.55)	(−4.17)	(−4.75)	(−3.95)
$\bar{R}^2$(%)	73.37	30.51	73.76	31.22	16.39	33.78	59.70	39.04	53.96	38.80	31.65	38.62

Panel 3. Trend regressions on residual idiosyncratic volatility

	Equal-weighted aggregate idiosyncratic volatility						Value-weighted aggregate idiosyncratic volatility					
	1945.01–2000.04			2000.05–2014.12			1945.01–2000.04			2000.05–2014.12		
	NYAXQ	NYAX	NASDQ	NYAXQ	NYAX	NASDQ	NYAXQ	NYAX	NASDQ	NYAXQ	NYAX	NASDQ
$\lambda(\times 10^5)$	0.21	0.07	0.35	0.85	0.31	1.01	0.13	0.09	0.75	0.93	0.38	1.54
	(0.93)	(0.46)	(0.86)	(0.80)	(0.42)	(0.83)	(0.68)	(0.40)	(0.77)	(0.98)	(0.87)	(0.84)
$\bar{R}^2$(%)	0.53	−0.02	3.46	0.05	−0.45	2.17	1.31	0.98	4.59	3.13	0.58	3.70

Panels 1&2 report the estimation results of the interaction regression and trend regression on the model-independent aggregate idiosyncratic volatility, while Panel 3 reports the estimation results of the trend regression on residual volatility. δ is the interaction parameter that measures the effect of price interaction on aggregate idiosyncratic volatility. λ is the trend parameter. The residual volatility series is computed as the estimated residuals from the interaction regression on the model-independent aggregate idiosyncratic volatility. The Newey and West (1987) adjusted *t*-statistics under the Bartlett kernel with the Newey–West fixed bandwidth are presented in parentheses below the coefficient estimate. Note that Bunzel and Vogelsang's (2005) 5% asymptotic critical value is 2.05 for the statistical significance of the trend parameter. $\bar{R}^2$(%) is the adjusted R^2 in percentage.

Appendix Table 2 Interaction regression on model-independent aggregate idiosyncratic volatility with control variables.

	Equal-weighted aggregate idiosyncratic volatility			Value-weighted aggregate idiosyncratic volatility		
	NYAXQ	NYAX	NASDQ	NYAXQ	NYAX	NASDQ
$\delta\ (\times 10^6)$	2.87	1.33	3.47	1.22	0.96	1.71
	(7.99)	(4.15)	(8.15)	(6.95)	(7.73)	(5.43)
γ_{AMH}	11.37	5.29	13.37	2.15	1.15	5.84
	(11.58)	(8.66)	(10.97)	(4.50)	(3.30)	(6.21)
γ_{ROA}	−0.11	−0.08	−0.13	−0.04	−0.03	−0.03
	(−0.92)	(−0.97)	(−0.94)	(−0.88)	(−0.71)	(−0.31)
$\gamma_{MTB}\ (\times 10^2)$	0.16	0.10	0.19	0.20	0.10	0.27
	(5.06)	(4.28)	(5.11)	(12.47)	(8.15)	(9.57)
$\gamma_{RND}\ (\times 10^2)$	0.26	−0.14	0.36	0.07	−0.10	0.17
	(0.87)	(−0.88)	(1.06)	(0.51)	(−0.90)	(0.95)
$\gamma_{GIP}\ (\times 10^2)$	0.00	−0.02	0.00	−0.02	−0.01	−0.04
	(−0.20)	(−0.99)	(−0.01)	(−2.25)	(−1.37)	(−2.21)
$\gamma_{DEF}\ (\times 10^2)$	0.42	0.64	0.36	0.10	0.09	0.03
	(3.72)	(10.42)	(2.69)	(3.03)	(2.65)	(0.60)
γ_{TMV}	−0.10	−0.01	−0.13	0.08	0.05	0.06
	(−1.85)	(−0.22)	(−2.24)	(1.35)	(0.79)	(1.14)
$\bar{R}^2$(%)	81.36	68.34	82.30	82.63	66.26	82.59

This table reports the estimation results of the interaction regression with the seven control variables on the model-independent aggregate idiosyncratic volatility. The interaction parameter δ measures the effect of price interaction on aggregate idiosyncratic volatility. AMH is the Amihud's (2002) illiquidity measure. ROA is the return on assets, MTB is the value-weighted firm level market value of assets over the book value of assets, RND is the value-weighted average of the scaled R&D expenditures, GIP is the growth rate in industrial production, DEF is the yield spread between BAA and AAA corporate bonds, and TMV is the realized variance of the value-weighted market returns. The Newey and West (1987) adjusted *t*-statistics under the Bartlett kernel with the Newey–West fixed bandwidth are presented in parentheses below the coefficient estimate. $\bar{R}^2$(%) is the adjusted R^2 in percentage.

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