2008 年度　ICS『資産価格の実証分析』

祝迫得夫

授業資料（第 8 回：12 月 2 日分）

１．　Chen, Roll, and Ross 他

２．抜粋：Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, (2001) "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk" Journal of Fiance, LVI, No. 1, 2001

Chen, Roll, and Ross

A	YP	IP	EI	UI	CG	GB	Constant
	4.341	13.984	−0.111	−0.672	7.941	−5.8	4.112
	(0.538)	(3.727)	(−1.499)	(−2.052)	(2.807)	(−1.844)	(1.334)
B	IP	EI	UI	CG	GB		Constant
	13.589	−0.125	−6.29	7.205	−5.211		4.124
	(3.561)	(−1.640)	(−1.979)	(2.590)	(−1.690)		(1.361)
C	EWNY	IP	EI	UI	CG	GB	Constant
	5.021	14.009	−0.128	−0.848	0.130	−5.017	6.409
	(1.218)	(3.774)	(−1.666)	(−2.541)	(2.855)	(−1.576)	(1.848)
D	VWNY	IP	EI	UI	CG	GB	Constant
	−2.403	11.756	−0.123	−0.795	8.724	−5.905	10.713
	(−0.633)	(3.054)	(−1.600)	(−2.376)	(2.972)	(−1.879)	(2.755)

Horse race (from Jagannathan and Wang 1997JF)

CAPM	**VW**					**R-square**
	-0.10					**1.35**
	(-0.28)					
CAPM + Size	**VW**	**Size**				**R-square**
	-0.32	**-0.11**				**57.56**
	(-0.94)	**(-2.30)**				
Fama-French	**VW**	**SMB**	**HML**			**R-square**
	-0.45	**0.33**	**-0.128**			**55.12**
	(-0.95)	**(1.530)**	**(-1.666)**			
Chen.Roll.Ross	**VW**	**IP**	**UI**	**CG**	**GB**	**R-square**
	-0.44	**-0.08**	**-0.77**	**0.930**	**-1.07**	**38.96**
	(-1.28)	**(-0.17)**	**(-1.95)**	**(1.630)**	**(-2.44)**	

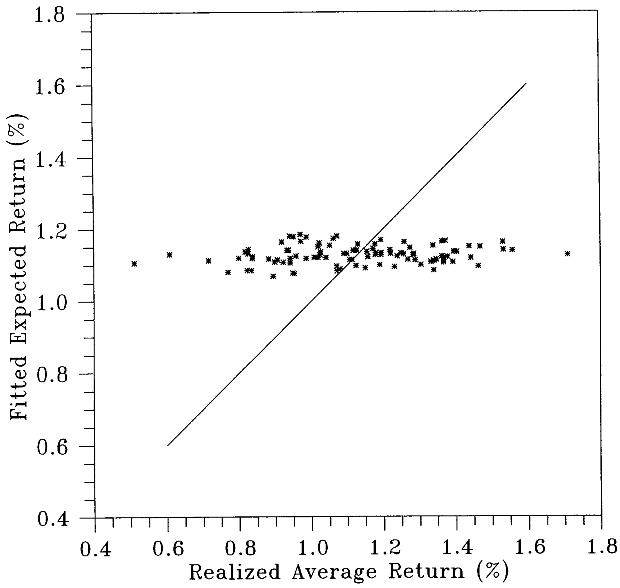


Figure 1. Fitted expected returns versus realized average returns. Each scatter point in the graph represents a portfolio, with the *realized average return* as the horizontal axis and the *fitted expected return* as the vertical axis. For each portfolio i, the realized average return is the time-series average of the portfolio return, and the fitted expected return is the fitted value for the expected return, $E[R_i]$, in the following regression model:

$$E[R_i] = c_0 + c_{vw}\beta_i^{vw},$$

where β_i^{vw} is the slope coefficient in the OLS regression of the portfolio return on a constant and the return on the value-weighted index portfolio of stocks. The straight line in the graph is the 45° line from the origin.

We may suspect that R_t^{labor} is the driving force behind the results for our main model. To determine if this is the case, we examine the following model:

$$E[R_{it}] = c_0 + c_{vw}\beta_i^{vw} + c_{labor}\beta_i^{labor}, \tag{31}$$

which can be obtained from the static CAPM by including the growth rate of labor income into the proxy for the market return. The estimated results for this specification are presented in Panel D of Table II. The coefficient corresponding to the growth rate of labor income is significant, both in the Fama-MacBeth regression and the GMM test using the HJ weighting matrix.[18] However, there is a strong residual size effect in the Fama-MacBeth regression. The HJ-distance is just slightly lower than that of model (28), and the

[18] Our empirical specification with labor income is similar to that used by Fama and Schwert (1977) when betas do not vary over time. The difference is that we use lagged labor income since labor income is published with a one-month lag. For a more detailed discussion of this issue, see Jagannathan and Wang (1993).

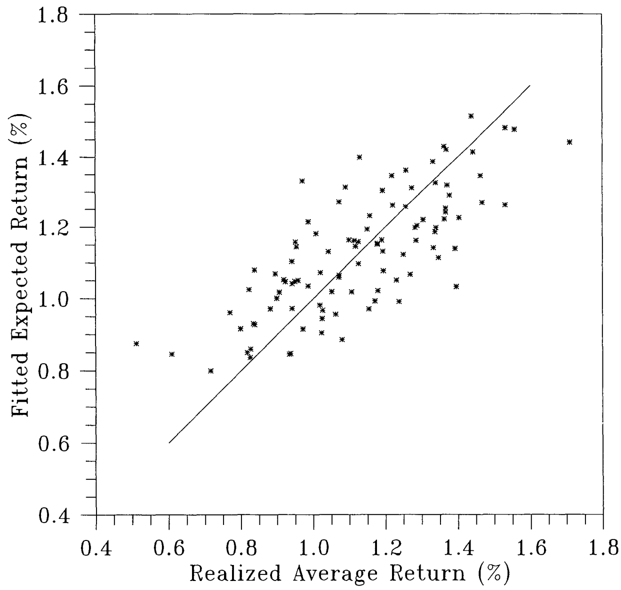


Figure 2. Fitted expected returns versus realized average returns. Each scatter point in the graph represents a portfolio, with the *realized average return* as the horizontal axis and the *fitted expected return* as the vertical axis. For each portfolio i, the realized average return is the time-series average of the portfolio return, and the fitted expected return is the fitted value for the expected return, $E[R_i]$, in the following regression model:

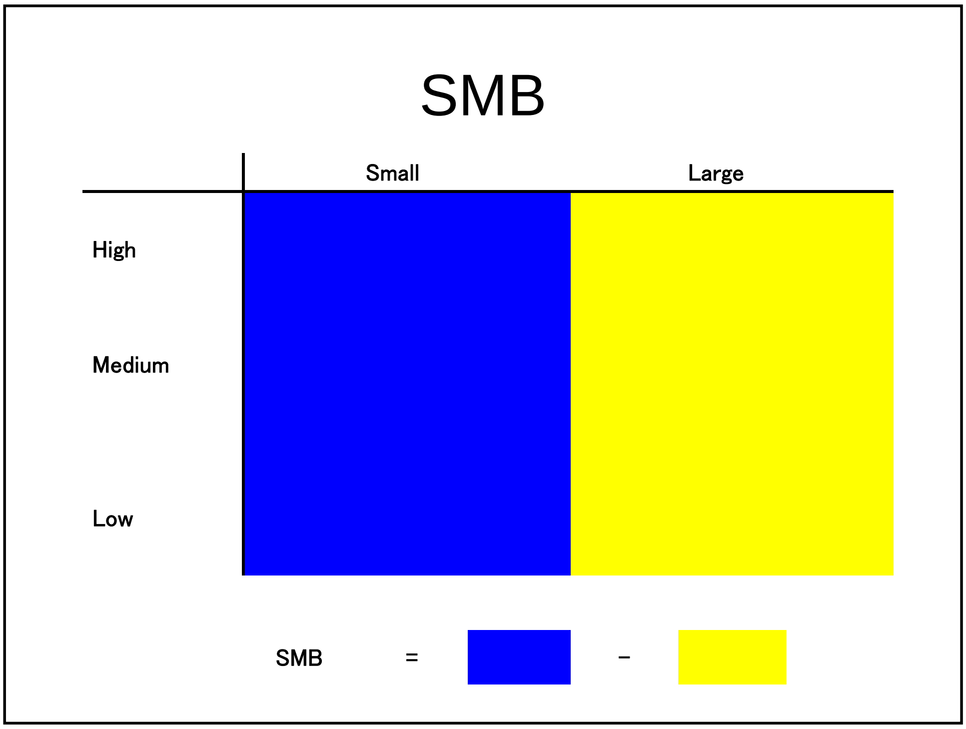
$$E[R_i] = c_0 + c_{\text{size}} \log(\text{ME}_i) + c_{\text{vw}}\beta_i^{\text{vw}},$$

where β_i^{vw} is the slope coefficient in the OLS regression of the portfolio return on a constant and the return on the value-weighted index portfolio of stocks, and the portfolio size, $\log(\text{ME}_i)$, is calculated as the equally-weighted average of the logarithm of the market value (in million dollars) of the stocks in portfolio i. The straight line in the graph is the 45° line from the origin.

p-value is only 1.94 percent. Thus, the pricing error of this model is still substantial. This suggests that it is necessary to allow for time variations in betas as well in order to explain the cross-section of expected returns on stocks.

C. Additional Investigations

The unconditional model we develop in this paper to some extent resembles the multi-factor model specified by Chen, Roll, and Ross (1986). A natural question that arises is whether the "lagged-prem factor" and the "labor-income-growth-rate factor" that we use in our specifications are just proxies for the macroeconomic factors that are identified by Chen, Roll, and Ross in their earlier work. Following them, we consider, besides the value-weighted stock index, four additional factors: (a) UTS_t is the monthly return spread between the long-term government bond and Treasury bill, (b) UPR_t is the return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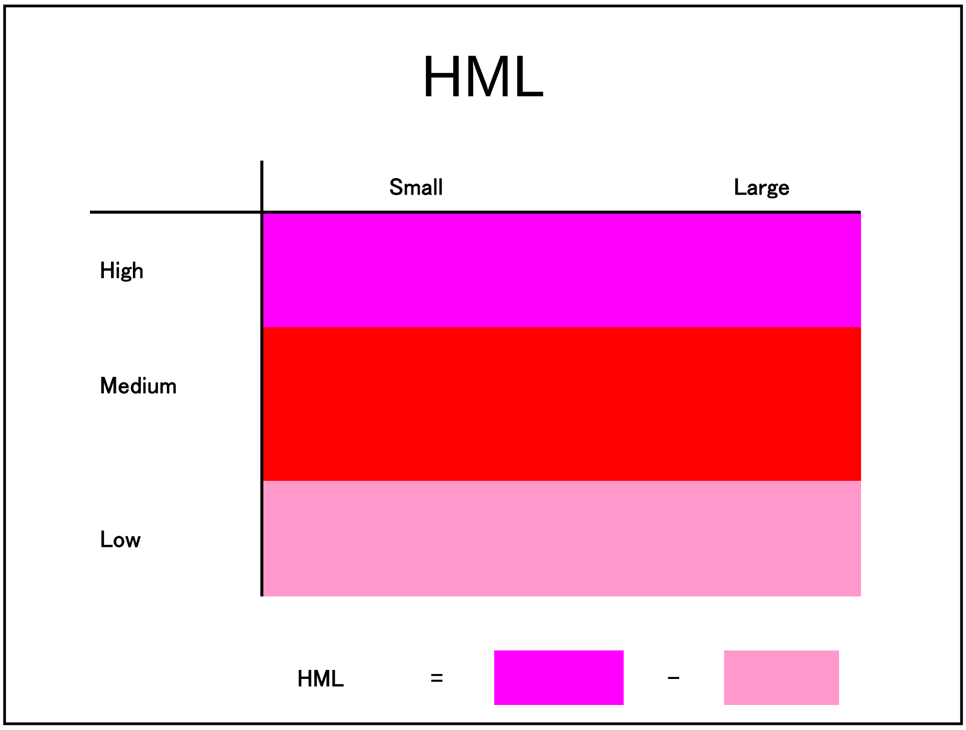
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Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk

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ABSTRACT

This paper uses a disaggregated approach to study the volatility of common stocks at the market, industry, and firm levels. Over the period from 1962 to 1997 there has been a noticeable increase in firm-level volatility relative to market volatility. Accordingly, correlations among individual stocks and the explanatory power of the market model for a typical stock have declined, whereas the number of stocks needed to achieve a given level of diversification has increased. All the volatility measures move together countercyclically and help to predict GDP growth. Market volatility tends to lead the other volatility series. Factors that may be responsible for these findings are suggested.

IT IS BY NOW A COMMONPLACE OBSERVATION that the volatility of the aggregate stock market is not constant, but changes over time. Economists have built increasingly sophisticated statistical models to capture this time variation in volatility. Simple filters such as the rolling standard deviation used by Officer (1973) have given way to parametric ARCH or stochastic-volatility models. Partial surveys of the enormous literature on these models are given by Bollerslev, Chou, and Kroner (1992), Hentschel (1995), Ghysels, Harvey, and Renault (1996), and Campbell, Lo, and MacKinlay (1997, Chapter 12).

Aggregate volatility is, of course, important in almost any theory of risk and return, and it is the volatility experienced by holders of aggregate index funds. But the aggregate market return is only one component of the return to an individual stock. Industry-level and idiosyncratic firm-level shocks are also important components of individual stock returns. There are several reasons to be interested in the volatilities of these components.

* John Y. Campbell is at Harvard University, Department of Economics and NBER; Lettau is at the Federal Reserve Bank of New York and CEPR; Malkiel is at Princeton University; and Xu is at the University of Texas at Dallas. This paper merges two independent projects, Campbell and Lettau (1999) and Malkiel and Xu (1999). Campbell and Lettau are grateful to Sangjoon Kim for his contributions to the first version of their paper, Campbell, Kim, and Lettau (1994). We thank two anonymous referees and René Stulz for useful comments and Benjamin Zhang for pointing out an error in a previous draft. Jung-Wook Kim and Matt Van Vlack provided able research assistance. The views are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of New York or the Federal Reserve System. Any errors and omissions are the responsibility of the authors.

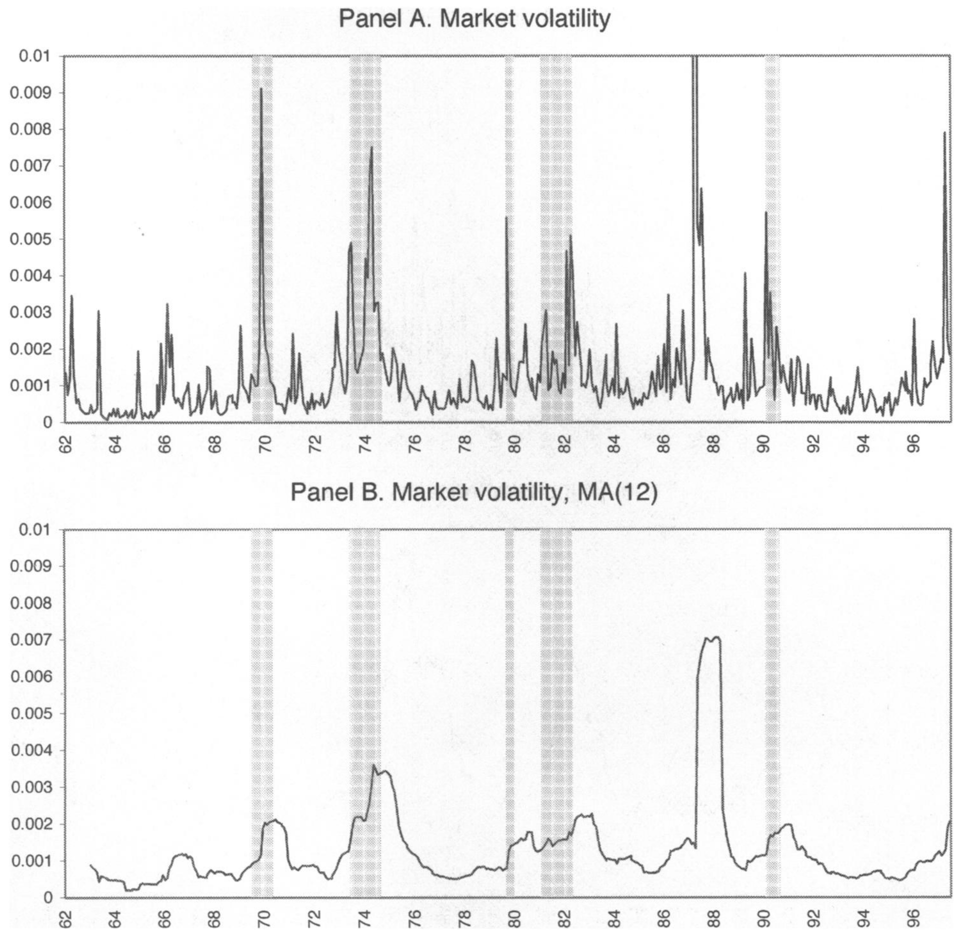

Figure 2. Annualized market volatility MKT. The top panel shows the annualized variance within each month of daily market returns, calculated using equation (17), for the period July 1962 to December 1997. The bottom panel shows a backwards 12-month moving average of MKT. NBER-dated recessions are shaded in gray to illustrate cyclical movements in volatility.

fair amount of high-frequency noise. Market volatility was particularly high around 1970, in the mid-1970s, around 1980, and at the very end of the sample. The stock market crash in October 1987 caused an enormous spike in market volatility which is cut off in the plot. The value of MKT in October 1987 is 0.672, about six times as high as the second highest value. The plot also shows NBER-dated recessions shaded in gray. A casual look at the plot suggests that market volatility increases in recessions. We will study the cyclical behavior of MKT and the other volatility measures below.

Next, consider the behavior of industry volatility IND in Figure 3. Compared with market volatility, industry volatility is slightly lower on average. As for MKT, there is a slow-moving component and some high-frequency

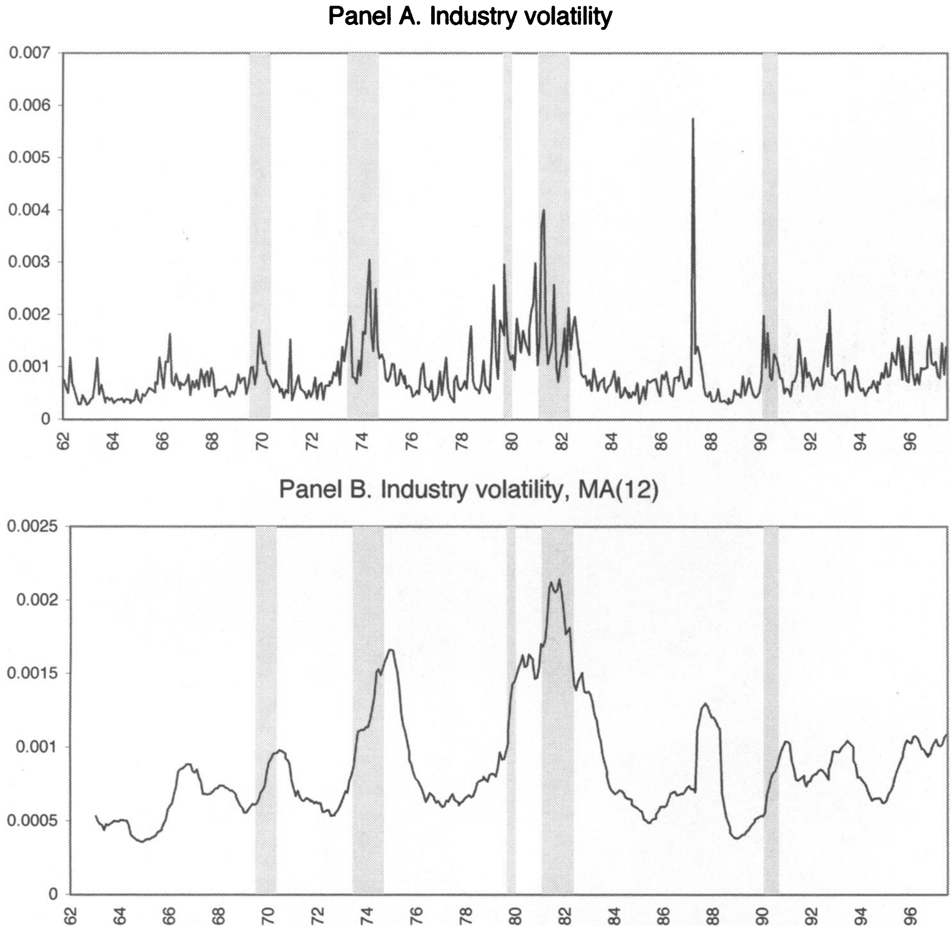

Figure 3. Annualized industry-level volatility IND. The top panel shows the annualized variance within each month of daily industry returns relative to the market, calculated using equations (18) and (19), for the period from July 1962 to December 1997. The bottom panel shows a backwards 12-month moving average of IND. NBER-dated recessions are shaded in gray to illustrate cyclical movements in volatility.

noise. IND was particularly high in the mid-1970s and around 1980. The effect of the crash in October 1987 is quite significant for IND, although not as much as for MKT. More generally, industry volatility seems to increase during macroeconomic downturns.

Figure 4 plots firm-level volatility FIRM. The first striking feature is that FIRM is on average much higher than MKT and IND. This implies that firm-specific volatility is the largest component of the total volatility of an average firm. The second important characteristic of FIRM is that it trends up over the sample. The plots of MKT and IND do not exhibit any visible upward slope whereas for FIRM it is clearly visible. This indicates that the

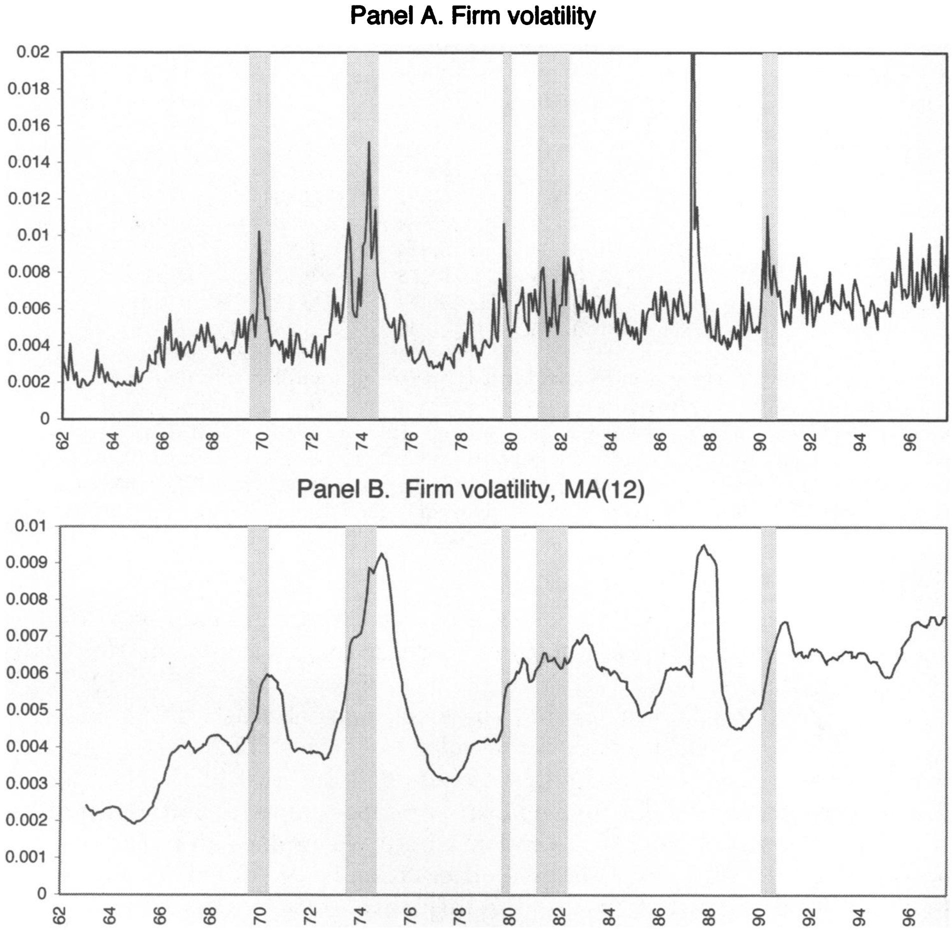

Figure 4. Annualized firm-level volatility FIRM. The top panel shows the annualized variance within each month of daily firm returns relative to the firm's industry, calculated using equations (20)–(22), for the period from July 1962 to December 1997. The bottom panel shows a backwards 12-month moving average of FIRM. NBER-dated recessions are shaded in gray to illustrate cyclical movements in volatility.

stock market has become more volatile over the sample but on a firm level instead of a market or industry level. Apart from the trend, the plot of FIRM looks similar to MKT and IND. Firm-level volatility seems to be higher in NBER-dated recessions and the crash also has a significant effect.

Looking at the three volatility plots together, it is clear that the different volatility measures tend to move together, particularly at lower frequencies. For example, all three volatility measures increase during the oil price shocks in the early to mid-1970s. However, there are also some periods in which the volatility measures move differently. For example, IND is very high compared to its long-term mean during the early 1980s while MKT and FIRM

Table IX

Cyclical Behavior: GDP Growth

GDP_{t-1}	RVW_{t-1}	MKT_{t-1}	IND_{t-1}	$FIRM_{t-1}$	R^2 (p-value)
0.330	0.020				0.143
(4.200)	(2.548)				
0.251	0.012	−0.701			0.190
(2.947)	(1.367)	(−2.383)			
0.211	0.015		−1.841		0.213
(2.270)	(1.762)		(−2.432)		
0.238	0.014			−0.477	0.206
(2.536)	(1.583)			(−2.999)	
0.199	0.013	−0.314	−1.470		0.219
(2.308)	(1.415)	(−0.883)	(−1.625)		(0.002)
0.236	0.013	−0.073		−0.441	0.206
(2.561)	(1.659)	(−0.180)		(−1.710)	(0.008)
0.201	0.013		−1.239	−0.250	0.222
(2.339)	(1.481)		(−1.184)	(−0.997)	(0.002)
0.200	0.013	−0.058	−1.237	−0.222	0.222
(2.135)	(1.532)	(−0.138)	(−1.249)	(−0.735)	(0.006)

Note: This table reports OLS regressions with GDP growth GDP_t as the dependent variable. All regressors are lagged by one quarter. MKT is market volatility constructed from equation (17), IND is industry-level volatility constructed from equations (18) and (19), and FIRM is firm-level volatility constructed from equations (20)–(22). All three measures are value-weighted variances, constructed from daily data downweighting the crash of October 1987, and are linearly detrended and time-aggregated to a quarterly frequency. RVW denotes the quarterly return on the CRSP value-weighted portfolio. Coefficients are reported with heteroskedasticity-consistent t-statistics in parentheses. The last column reports the regression R^2 and the p-value for a heteroskedasticity-consistent test of the joint significance of the volatility measures.

C. Cyclical Behavior of Volatility Measures in Individual Industries

In the previous section, we showed that aggregate volatility measures are strongly countercyclical and have some ability to forecast aggregate GDP growth. Now we examine whether there are similar patterns on the level of individual industries. Because output data for individual industries are only available on an annual basis, we convert all volatility series accordingly. The output data were obtained from the BLS and range from 1972 to 1997. Data for industries 23 (miscellaneous manufacturing) and 49 (miscellaneous firms) were not available. To construct industry-specific output data we first regress the output growth rate in industry i, Δy_{it}, on total industrial output growth Δy_t. Denote the industry-specific residual ν_{it}. Table X reports simple correlations of ν_{it} with contemporaneous and one-period lagged industry and firm-specific volatility for the 10 largest industries. Almost all of the corre-