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The Rise in Firm-Level Volatility: Causes and Consequences

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1 Introduction

Over the past thirty years, there has been a decline in aggregate volatility (McConnell and Perez-Quiros 2000, Stock and Watson 2002). At the same time, there has been a large increase in the volatility of firms (Comin 2000; Campbell, Lettau, Malkiel, and Xu 2001; Comin and Mulani 2003; and Chaney, Gabaix, and Philippon 2002).

Our paper has five parts. We first document the upward trend in various measures of firm volatility. Second, we present a decomposition of aggregate volatility between the average volatility of sectors and the correlation of growth across sectors. This decomposition suggests that the decline in aggregate volatility is mostly due to a decline in the correlation growth rates across sectors.

Third, we explore whether the firm-level trend toward more volatility and the aggregate trend toward more stability are related, or whether the two have moved in opposite directions by coincidence. The two trends appear to be related. We find that TFP growth in industries where firms have become more volatile tends to be less correlated with aggregate TFP growth. Across countries, there also seems to be a negative relationship between aggregate and firm-level volatility.

Fourth, we explore the potential explanations for the increase in firm-level volatility. We find support for the idea that firm volatility has increased because of higher competition in the goods market. We find that firm volatility increases after deregulation. We also find that the increase in firm-level volatility is correlated with high research and development (R&D) activity as well as more access to debt and equity markets. However, we find no evidence that sectors with more access to external finance have become less correlated with the rest of the economy, while we do find evidence that sectors with larger increases in R&D investment have become less correlated with the rest of the economy.

2 The Facts

The decline in aggregate volatility has been documented by McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), and Stock and Watson (2002). On the other hand, firm-level volatility has increased. Firm-level volatility can be measured using financial data or real data. Using financial data for the United States, Comin (2000) and Campbell, Lettau, Malkiel, and Xu (2001) document an increase in the volatility of idiosyncratic stock returns. Using accounting data, Chaney, Gabaix, and Philippon (2002) and Comin and Mulani (2003) show an increase in the idiosyncratic volatility of employment, sales, earnings, and capital expenditures.

Throughout the paper, we will use aggregate data from the National Income and Product Accounts and firm-level data from COMPUSTAT and CRSP. We will also use the sectoral data set developed by Jorgenson and Stiroh (from now on, KLEM data).[1]

2.1 *Volatility: GDP Versus Firm Sales*

In this section, we document the increase in firm volatility using real measures, like sales, employment, or capital expenditures. Our sample includes all the firms in COMPUSTAT with at least eleven consecutive observations of the relevant variable. Table 3.1 contains the basic descriptive statistics for our sample.

Figure 3.1 shows the evolution of idiosyncratic and aggregate volatility. Aggregate volatility (σ_t^a) is defined as the standard deviation of the annual growth rate (γ_t) of real GDP:

$$\sigma_t^a = \left[\frac{1}{10}\sum_{\tau=-4}^{+5}(\gamma_{t+\tau} - \bar{\gamma}_t)^2\right]^{1/2} \tag{3.1}$$

where $\bar{\gamma}_t$ is the average growth rate between $t-4$ and $t+5$. For each firm i, we compute the volatility of the growth rate of sales ($\gamma_{t,i}$) as:

$$\sigma_{i,t} = \left[\frac{1}{10}\sum_{\tau=-4}^{+5}(\gamma_{t+\tau,i} - \bar{\gamma}_{t,i})^2\right]^{1/2} \tag{3.2}$$

Table 3.1
Firm-Level Summary Statistics

Year	Number of Firms	Average Real Sales	Median Sales Volatility
1955	810	1.30	0.096
1956	829	1.35	0.093
1957	849	1.38	0.090
1958	927	1.22	0.084
1959	982	1.28	0.081
1960	1,589	0.87	0.095
1961	1,727	0.84	0.098
1962	1,952	0.82	0.099
1963	2,171	0.81	0.099
1964	2,351	0.83	0.098
1965	2,506	0.86	0.100
1966	2,680	0.89	0.108
1967	2,861	0.89	0.114
1968	3,450	0.82	0.120
1969	3,633	0.92	0.122
1970	3,705	0.91	0.128
1971	3,898	0.92	0.141
1972	4,073	0.96	0.139
1973	4,502	1.02	0.134
1974	6,110	0.88	0.139
1975	6,175	0.84	0.138
1976	6,224	0.91	0.139
1977	6,262	0.97	0.142
1978	6,187	1.04	0.146
1979	6,081	1.15	0.149
1980	6,187	1.18	0.151
1981	6,226	1.17	0.157
1982	6,530	1.09	0.167
1983	6,771	1.05	0.174
1984	6,827	1.09	0.179
1985	7,135	1.06	0.184
1986	7,394	1.03	0.188
1987	7,448	1.11	0.190
1988	7,295	1.20	0.192
1989	7,202	1.27	0.187
1990	7,239	1.33	0.181
1991	7,375	1.27	0.175

Table 3.1
(continued)

Year	Number of Firms	Average Real Sales	Median Sales Volatility
1992	7,786	1.22	0.171
1993	8,907	1.11	0.160
1994	9,288	1.17	0.163
1995	10,101	1.18	0.172
1996	10,282	1.23	0.180
1997	10,020	1.33	0.197
1998	10,286	1.39	0.212
1999	10,294	1.51	0.211
2000	9,819	1.76	0.207

Average sales in 2000 in billions of dollars.

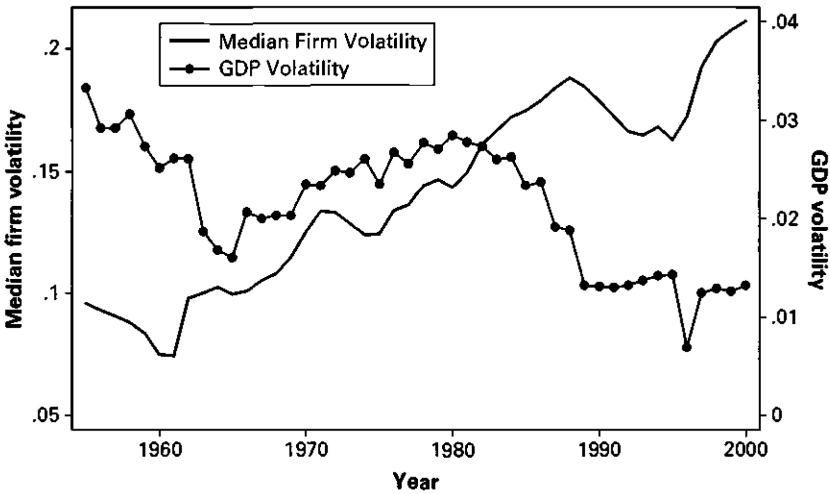

Figure 3.1
GDP Versus Individual Firm Sales Volatility: 10-Year Centered Rolling Standard Deviation of Growth Rates

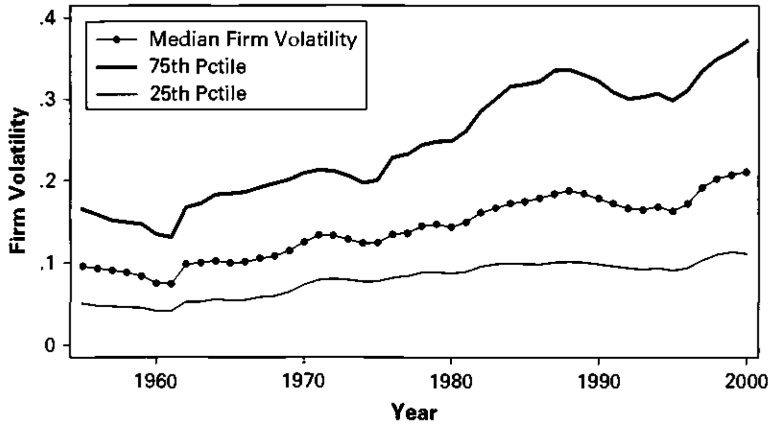

Figure 3.2
Distribution of Firm Volatility: 10-Year Centered Rolling Standard Deviation of Sales Growth

We then take the median across all firms present in the sample at time t as our measure of typical firm volatility:

$$\sigma_t^f = \text{median}_i\{\sigma_{i,t}\}$$

Figure 3.1 shows the decline in σ_t^a and the increase in σ_t^f. Note also the difference of scale between the two measures. Idiosyncratic volatility is an order of magnitude larger than aggregate volatility.[2] Figure 3.2 shows the evolution of the 25th and 75th percentiles of the distribution of firm volatility. It is clear that the whole distribution has moved upward and that the increase in volatility is even more pronounced at the top.[3]

Our first task is to show the robustness of these findings. The main issues are sample selection bias and measurement errors. Sample selection is an issue because more small firms have entered the COMPUSTAT database over time. Since small firms tend to be more volatile, the changing composition could explain the trend. We deal with this first issue by controlling for size and age, and showing that the increase in firm volatility holds within groups of comparable firms. Comin and Mulani (2003) also show that the results are robust to the inclusion of firms' fixed effects.[4]

The second issue is whether firm-level results are economically meaningful. To take an extreme example, suppose that we live in a world of constant returns without financial frictions or incentive

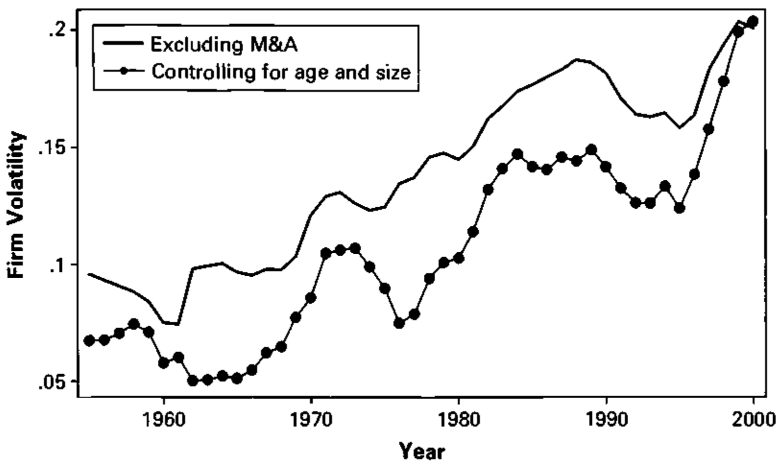

Figure 3.3
Firm Volatility, Alternative Measures: Ten-Year Centered Rolling Standard Deviation of Sales Growth

problems, in which boundaries of organizations do not matter. Plants could move among firms without any real consequences, yet firms would appear to be volatile. Firms would simply not be the right units of observation. One could perhaps argue that mergers and acquisitions (M&As) fall partly into the category of irrelevant ownership changes. Thus, as a robustness check, we are going to show that our results are not driven by M&As.

Figure 3.3 shows that the trend increase in firm volatility is not driven by the entry of young and small firms, or by an upsurge in M&A activity.[5] Another way to show that our results are economically meaningful is to show that they relate to results obtained in other data sets. Guvenen and Philippon (2005) show that firm volatility measured across industries in COMPUSTAT is a good predictor of both unemployment risk and wage inequality measured across the same industries in PSID. Comin, Groshen, and Rabin (2005) relate firm-level volatility to wage volatility at the occupation level by taking advantage of a unique data set that contains firm-level and worker-level information for a sample of firms in Ohio. They document a positive relationship between firm-level volatility and the volatility and dispersion of wages at the occupation level. We will not discuss these results further, but we note that they show that our measures of volatility capture real economic risks, not just measurement error or sample composition bias.

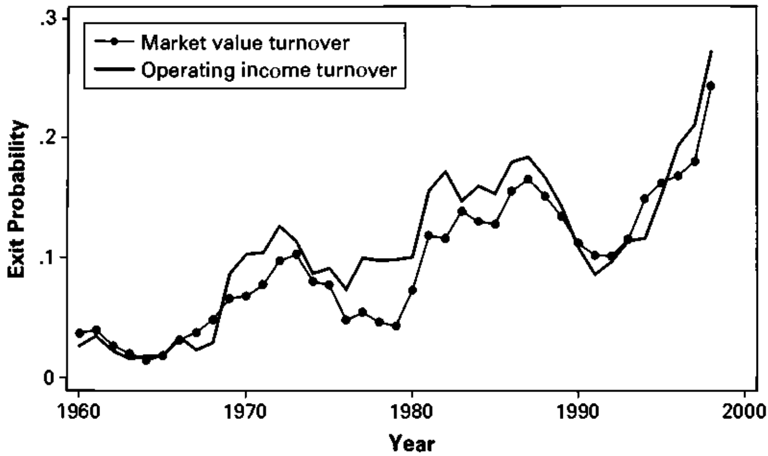

Figure 3.4
Turnover of Industry Leaders: 5-Year Ahead Exit Rate from Top 20% of Industry

2.2 *Turnover of Leaders Within Industries*

The distribution of firm sizes is famously skewed, and a few firms account for most of the sales in each industry. Thus, one might argue that firm volatility is relevant only if it affects the industry leaders. We define turnover in industry I at time t as the probability of leaving the top quintile of the industry over a five-year period:

$$TopTurn_{I,t} = P(Z_{it+5} < Z_{t+5}^{top,I(i)} \mid Z_{it} > Z_t^{top,I(i)})$$

where Z_{it} is either operating income or market value of firm i at time t, and $Z_t^{top,I(i)}$ is the 80th percentile of the distribution of Z_{it} at time t in industry $I(i)$. This measure is robust to the entry of small firms in the particular industry. We then define average turnover as the median of turnover across all industries.

Figure 3.4 shows the increase in turnover among leaders for both operating income and market value. There are too few firms in the sample in the 1950s to obtain a reasonable estimate of the probability, so we also computed the correlation of ranking over time, using all the firms and not only the top 20 percent. For a particular measure Z, we define:

$$RkCorr = Corr_{i \in I}(rank_{I,t}(Z_{it}), rank_{I,t}(Z_{it+\tau}))$$

where $rank_{I,t}(Z_{it})$ is the rank of firm i in industry I at time t according to Z. The picture using market value or operating income is similar to

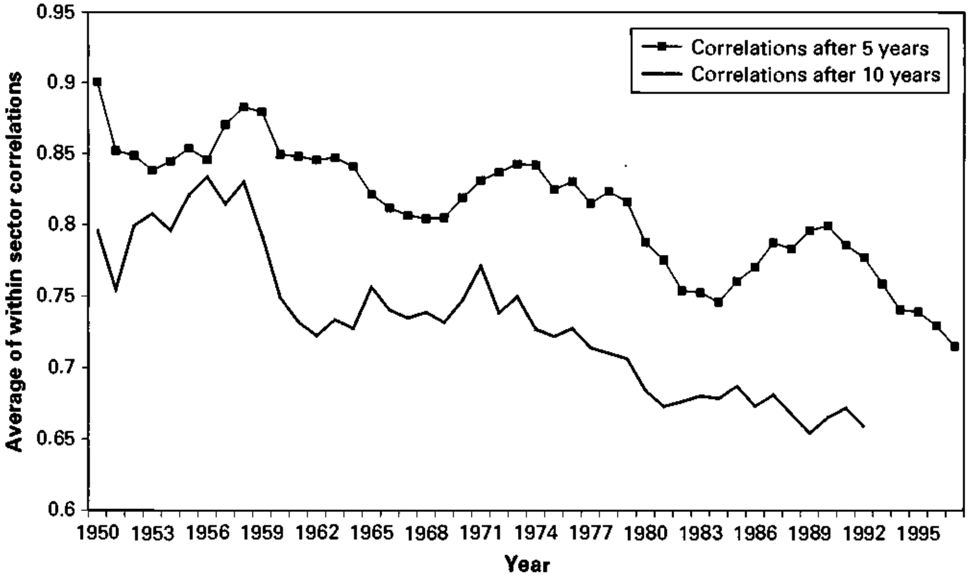

Figure 3.5
Correlation of Labor Productivity Rankings
Note: Five and ten years ahead correlation of within sector ranking, based on sales per employee.

the one in figure 3.4 and, for the sake of completeness, we present the results based on labor productivity rankings.

Figure 3.5 shows the evolution of the ranking correlation of firms, over five and ten years, based on labor productivity. There has been a clear decline in the ranking correlations over time. We will return to the interpretation of these findings when we discuss product market competition.

2.3 *Equity Return Volatility*

Real data are probably more directly relevant for macroeconomics. However, there are at least two good reasons to explore financial data as well. The first is that financial data will allow us to look at firm volatility before World War II. The second is that financial data can help us disentangle risk from predictable variations in firm dynamics.

We start by looking at equity returns. Let $r_{i,t,m}$ be the return to shareholders of firm i in month m of year t, and let $r_{t,m}^{VW}$ be the monthly return on the Value Weighted Index. All the returns come from CRSP.

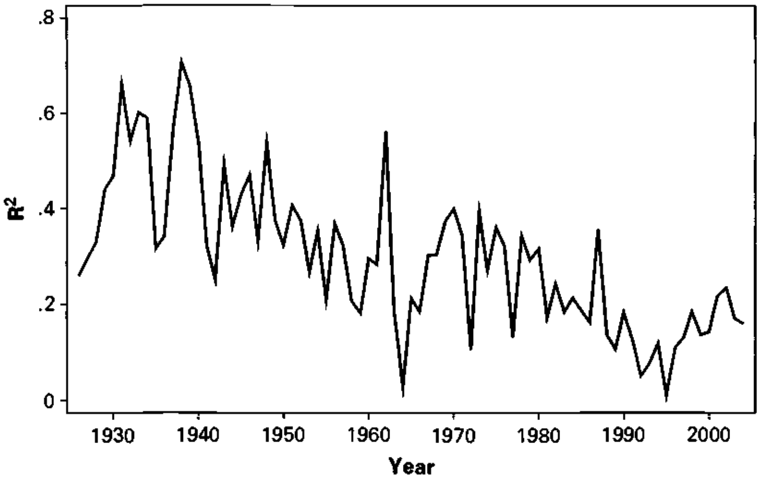

Figure 3.6
The Declining Explanatory Power of CAPM: Mean R^2 from CAPM on Monthly Returns
Note: For each firm/year, the CAPM-beta is estimated using 12 monthly returns.

For each firm, we estimate the CAPM model over rolling windows of thirty-six months:

$$r_{i,t,m} = \beta_{i,t} r_{t,m}^{VW} + \varepsilon_{i,t,m}, \qquad \text{for } m = 1, \dots, 12$$

We therefore allow $\beta_{i,t}$ to vary (smoothly) over time, as seems plausible since we use data from 1926 to 2004. We take the median across all firms/months observations in year t as our measure of idiosyncratic financial volatility:

$$\sigma_t^{fin} = \text{median}_{i,m}(|\varepsilon_{i,t,m}|)$$

The nice thing about monthly data is that it allows us to construct non-overlapping annual measures of firm volatility. We define the explanatory power of the CAPM model as the share of total firm return volatility that one can explain with the market return, i.e., the R^2 of the CAPM regression.

Figure 3.6 shows the historical decline in the explanatory power of CAPM. CAPM used to explain 40 percent of firm returns before the 1950s, but its explanatory power is now around 10 percent. R^2 is the ratio of two volatilities, however, and we also want to know what has happened to the level of idiosyncratic volatility. Figure 3.7 shows a U-shaped pattern for σ_t^{fin}. Firm volatility was high in the late 1920s, and it

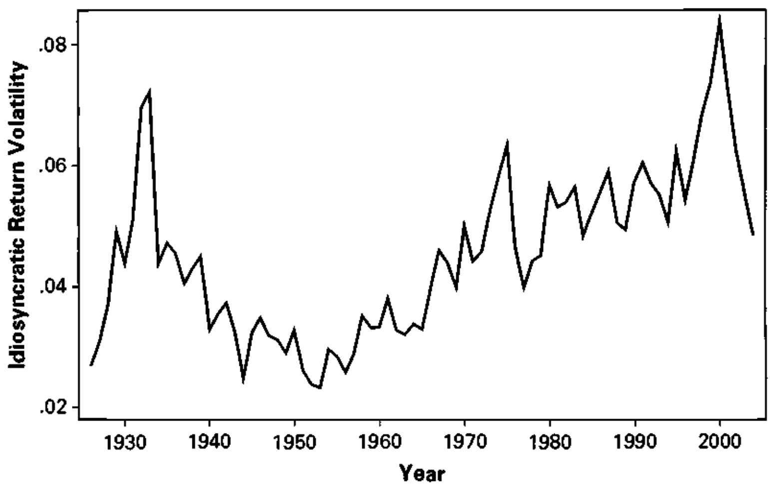

Figure 3.7
The Evolution of Idiosyncratic Return Volatility: Median Absolute Deviation of Monthly Residual Firm Returns
Note: Firm returns are CAPM-adjusted using betas estimated on 12 monthly returns.

increased dramatically during the market crash and the early years of the great depression. It then declined steadily from the mid-1930s to the mid-1950s. At that point in time, we can make the link with the real data presented in the previous section. Since the mid-1950s, both real and financial volatility have increased steadily, with large spikes around the first oil shock and the rise and fall of the Internet bubble. For a discussion of the link between financial and real volatility at the firm level, see Veronesi and Pastor (2003).

Finally, note that our measure of firm volatility falls from 2001 to 2003. First, many firms have delisted from the stock exchanges, and delisting is more common for small, risky firms. Second, holding constant the composition of the sample, there has been a decrease in firm volatility. This is not unprecedented. The same happened in the early 1990s, and we expect firm volatility to start increasing again in the near future.

2.4 *Credit Ratings and Credit Spreads*

If firms have really become more risky, then this should also be reflected in corporate bond spreads and corporate bond ratings. For the spread, we use Moody's seasoned Aaa corporate bond yield minus the ten-year treasury rate. For bond ratings, we use S&P long-term do-

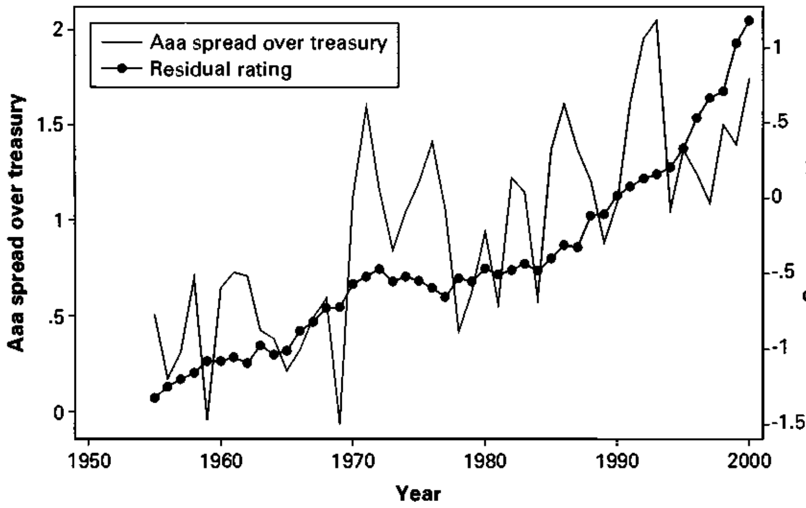

Figure 3.8
Average Credit Ratings and Credit Spreads
Note: Rating ranges from 2 (AAA) to 20 (CCC). Index adjusted for age, size, and industry.

mestic issuer credit rating from COMPUSTAT, coded from 2 for AAA to 27 for D (default). We first regress the rating on firm-level characteristics (age, assets, sales, SIC code), and we then average the residuals across firms. Figure 3.8 shows that the Aaa spread over treasury has increased overtime, and also that the average credit rating of firms in COMPUSTAT has deteriorated. Both trends suggest an increase in risk, consistent with the increase in cash flow volatility. For more on this topic, see Campbell and Taksler (2003).

Historical default rates on corporate bonds have also varied a lot over time. The average default rate from 1900 to 1943 was 1.7 percent. It dropped to a mere 0.1 percent from 1945 to 1965 (Sylla 2002). It then increase again, to 0.64 percent between 1970 and 1985, and to 1.85 percent between 1986 and 2001 (Moody's 2002). These evolutions are also consistent with the importance of rating agencies. These agencies played an important role before World War II, became largely irrelevant in the 1950s and 1960s, and have regained their previous importance in the past thirty years (Sylla 2002).

Conclusion 1: Firm-level risk has increased over the past fifty years.

Conclusion 2: Firm-level risk was higher in the 1920s and 1930s than in the 1950s and 1960s.

3 Sectoral Evidence

We have established that the aggregate stabilization of the U.S. economy has coincided with a large increase in firm-level risk. However, in a statistical sense, this is only one observation. Our goal in this section is to explore sectoral dynamics and see how they relate to firm volatility. We are first going to show that the decline in aggregate volatility is accounted for by a decrease in the comovement of the different sectors and not by a decrease in the average volatility of each sector. Second, we are going to show that sectors in which firms have become more volatile have typically become less correlated with the aggregate. Sectoral data comes from Jorgenson and Stiroh's 35 KLEM data set.[6]

3.1 Decomposition of Aggregate Volatility

We now perform a decomposition of the aggregate variance of the growth rate of real value added, TFP, and real value added per worker into sector variances and correlations. Let $\gamma_{s,t}$ be the growth rate of the particular variable in sector s at time t, and let ω_{st}^{sec} be the share of sales for sector s in the aggregate sales in the economy. Also, let $V([Z_\tau]_{t-4}^{t+5})$ denote the variance of $\{Z_{t-4}, Z_{t-3}, \ldots Z_t, \ldots Z_{t+4}, Z_{t+5}\}$ for any generic variable Z and $Cov([Z_\tau]_{t-4}^{t+5}, [Y_\tau]_{t-4}^{t+5})$ be the covariance between $\{Z_{t-4}, Z_{t-3}, \ldots Z_t, \ldots Z_{t+4}, Z_{t+5}\}$ and $\{Y_{t-4}, Y_{t-3}, \ldots Y_t, \ldots Y_{t+4}, Y_{t+5}\}$. By definition, the aggregate growth rate is:

$$\gamma_t = \sum_i \gamma_{s,t}\omega_{s,t}^{\text{sec}}$$

Then, using the definition of the variance:

$$V([\gamma_\tau]_{t-4}^{t+5}) \equiv \frac{1}{10}\sum_{\tau=t-4}^{t+5}\left(\sum_i \gamma_{s,\tau}\omega_{s,\tau}^{\text{sec}} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\sum_i \gamma_{s,\tau}\omega_{s,\tau}^{\text{sec}}\right)^2$$

For simplicity, suppose that $\omega_{s,t}^{\text{sec}} = \omega_s^{\text{sec}}$ for all the sectors i and all years t. Then $V([\gamma_\tau]_{t-4}^{t+5})$ can be written as follows:[7]

$$V([\gamma_\tau]_{t-4}^{t+5}) = \underbrace{\sum_s (\omega_s^{\text{sec}})^2 V([\gamma_{s,\tau}]_{t-4}^{t+5})}_{\text{Variance Component}} + \underbrace{\sum_s \sum_{j\neq s} \omega_s^{\text{sec}}\omega_j^{\text{sec}}\, Cov([\gamma_{s,\tau}]_{t-4}^{t+5}, [\gamma_{j,\tau}]_{t-4}^{t+5})}_{\text{Covariance Component}}$$

Hence, the variance of the growth rate of aggregate sales is decomposed into two terms: the first is related to the sector level variance of sales (variance component), and the second reflects the covariances between the growth rates of sales at different sectors (covariance component).

The first two rows in figure 3.9 show the evolution of the variance and covariance components of the variance of the growth rate of aggregate value added, aggregate value added per worker, and TFP. The variance component of all three variables displays a hump-shaped pattern over time, with no obvious decline over our sample period, 1959 to 1996. On the other hand, for all three variables, we can observe that there has been a decline since the 1970s in the covariance of growth across sectors. For value added per worker and TFP, there has been an important decline in the covariance of growth over our sample period, while for value added growth there has been no trend.

For the three variables, the covariance component is substantially larger than the variance component. The difference in magnitude ranges from twice larger (TFP growth) to an order of magnitude larger (value added growth). As a result, the relevant component for understanding the dynamics of aggregate volatility is the covariance of growth across sectors.

The covariance component is affected by the sectoral variance and by the correlation of a sector with the others. To increase further our understanding, we also compute the correlation component. Specifically, we define first the correlation of each sector with the other sectors:

$$Corr_{s,t}^{\text{sec}} = \sum_{j \neq s} \frac{\omega_j^{\text{sec}}}{\sum_{h \neq s} \omega_h^{\text{sec}}} \, Corr([y_{s,\tau}]_{t-4}^{t+5}, [y_{j,\tau}]_{t-4}^{t+5}) \tag{3.3}$$

Then we define aggregate correlation as a weighted average of the sectoral correlations:

$$Corr_t^a = \sum_s \omega_s^{\text{sec}} \, Corr_{s,t}^{\text{sec}}$$

The third row in figure 3.9 shows a clear decline in aggregate correlation for value added, TFP, and value added per worker growth over time. Hence, we conclude that, in order to understand the decline in aggregate volatility, we should try to understand what drives this decline in the correlation between sectors. The results presented in this section are based on the KLEM sectoral data set. We have obtained similar results for the decomposition of aggregate volatility using manufacturing data from the BLS.

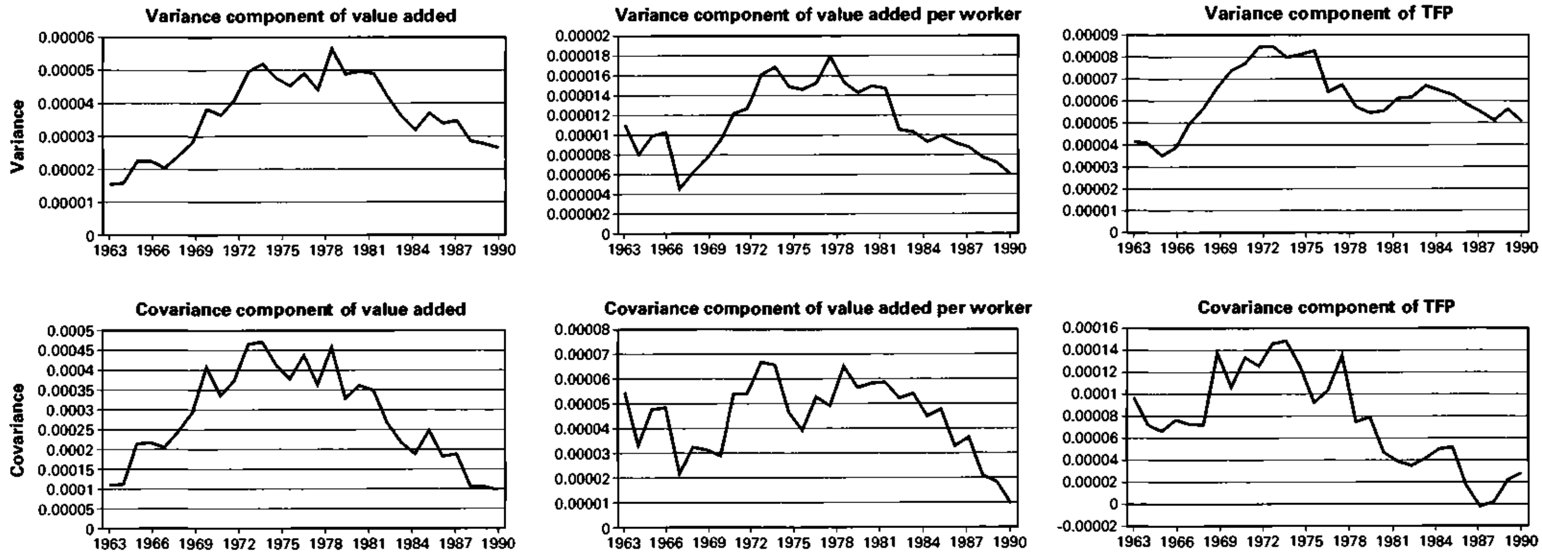

Figure 3.9
Variance-Covariance-Correlation

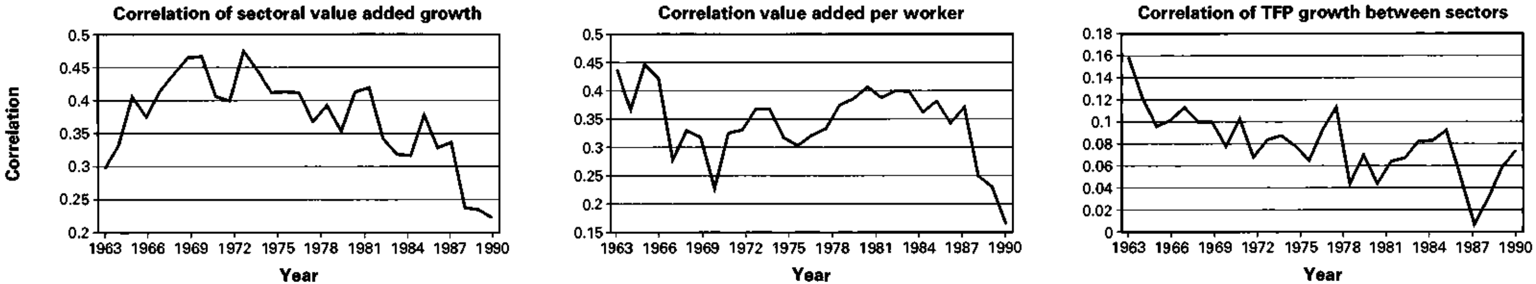

Figure 3.9
(continued)

Table 3.2
Sectoral Correlation and Firm Volatility, Panel Regression, Thirty-Five Sectors

Dependent Variable	Sectoral Correlation of Growth in Value Added	Sectoral Correlation of Growth in Employment	Sectoral Correlation of Growth in Labor Productivity	Sectoral Correlation of Growth in TFP
Average firm volatility	−0.036 (0.096)	−0.23 (.12)	−0.264 (.126)	−0.22 (.08)
N	1011	1011	1011	1011

Firm volatility measured in COMPUSTAT. Sector correlation measured in Jorgenson's data set. All regressions include a time trend and sector fixed effects. Newey-West standard errors in parentheses.

Conclusion 3: The decline in aggregate volatility is mostly due to a decrease in the correlation of growth rates across sectors. The contribution of average sector volatility is less important.

3.2 *Firm Volatility and Sector Comovements*

We now ask if the decline in comovement across sectors is linked to the increase in volatility within each sector. We start from our measure of idiosyncratic firm volatility $\sigma_{i,t}$ defined in equation (2). We aggregate this measure within each sector to obtain a sector-specific measure of firm volatility:

$$\sigma^{sec}_{s,t} = mean_{i \in s}(\sigma_{i,t})$$

On the other hand, we have the sector-specific correlation measure, $Corr^{sec}_{s,t}$, defined in equation (3). We run the following regressions:

$$Corr^{sec}_{s,t} = \alpha_i + \beta t + \gamma \sigma^{sec}_{s,t} + \varepsilon_{s,t}$$

Table 3.2 shows the results when the dependent variable is the correlation of value added, employment, labor productivity, and TFP. We estimate a negative γ in all specifications, and it is significant for the last three. Of course since both $\sigma^{sec}_{s,t}$ and $Corr^{sec}_{s,t}$ are autocorrelated, we use Newey-West to assess the significance of β. As a robustness check, we estimate the relationship between sectoral correlation and firm volatility, replacing the time trend by sector dummies. In this alternative specification, we continue to obtain a negative estimate of γ that is statistically significant.

To have a more graphical image of the relationship between firm volatility and sectoral correlation, figures 3.10a and 3.10b show the

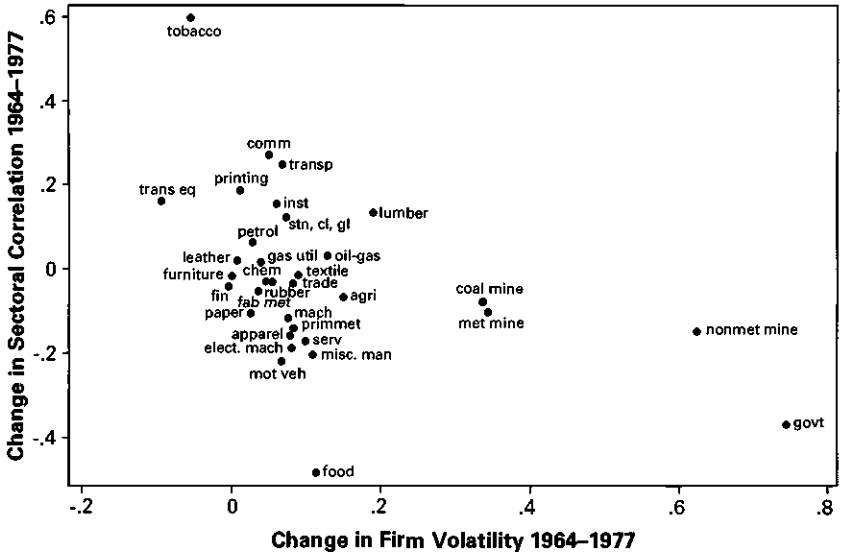

Figure 3.10a
Firm Volatility and Sectoral Correlation, 1964–1977

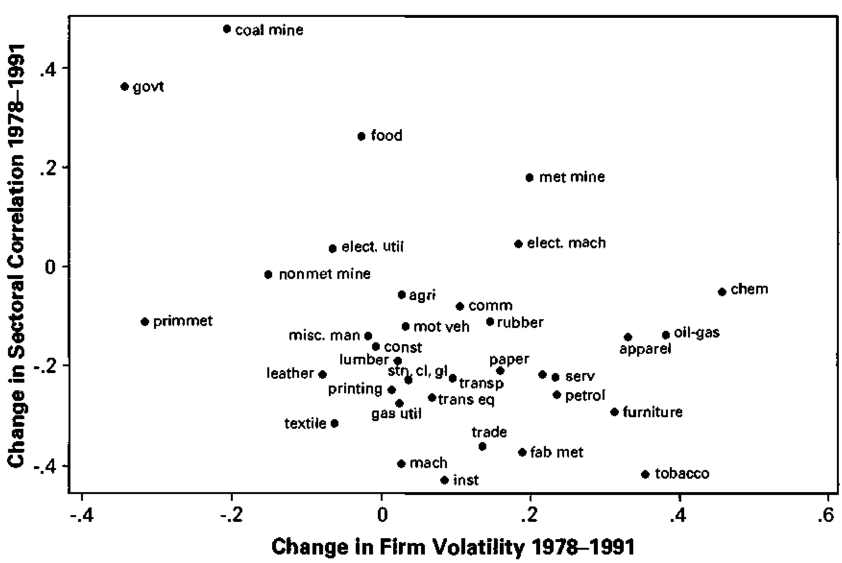

Figure 3.10b
Firm Volatility and Sectoral Correlation, 1978–1991

change in the correlation of output per worker against the change in the volatility of firms between 1964 and 1977 and between 1978 and 1991, respectively, for the thirty-five sectors in our sample. In these figures, there is a clear and significant negative cross-sectional relationship between the change in firm volatility and the change in sectoral correlation for the two periods that cover the whole time-span of our sample. In various robustness checks, we have found that the results for productivity (either value added per worker, or TFP) are robust, while the results for quantities (either employment or value added) are not always significant.

Conclusion 4: Comovement has decreased more in sectors where firm volatility has increased more.

4 International Evidence

So far our exploration has been restricted to the United States because of data availability. Some research, however, has been done on non-U.S. data. Frazzini and Marsh (2002) do not find the same increase in firm volatility in the United Kingdom. Thesmar and Thoenig (2004) show an increase in France, especially for listed firms. Li, Morck, Yang, and Yeung (2004) show that the CAPM explains a larger part of firm equity returns in emerging markets than in developed economies.

Adding to this evidence, we explore the evolution of firm-level volatility using a short panel of international firms in the COMPUSTAT GLOBAL data set. This sample covers publicly traded companies between 1993 and 2004 in more than eighty countries, representing over 90 percent of the world's market capitalization, including coverage of over 96 percent of European market capitalization and 88 percent of Asian market capitalization. Due to the short nature of the panel, we compute volatility using four-year rolling windows. Specifically, for every firm in the sample, we compute the standard deviation of the growth rate of employment on a rolling window of four consecutive years. Our measure of firm volatility in year t is either the mean or the median of the standard deviations across all firm in year t. Table 3.3 reports the evolution of these measures of firm volatility. We can observe a clear increase in both measures of firm-level volatility during the 1990s. Unfortunately, the panel is too short to see if the upward trend in firm volatility holds in the postwar period.

The length of the panel limits the time series exploration of firm volatility, but it does not preclude us from investigating the cross-section

Table 3.3
Firm-Level Volatility in the World

Year	Number of Firms	Median Volatility	Average Volatility
1995	2,685	0.0694	0.1301
1996	2,752	0.0737	0.1417
1997	2,762	0.0872	0.1587
1998	3,429	0.0999	0.1859
1999	3,652	0.1126	0.1983
2000	3,711	0.1205	0.2161
2001	1,831	0.1281	0.2269

determinants of volatility. In particular, one interesting issue that we can address is the relationship between income per capita and volatility. At the aggregate level, figure 3.11a shows a well-known fact from, for example, Acemoglu and Zilibotti (1997): namely, that there is a negative relationship between the volatility and the initial level of income per capita. In this case, the sample contains a cross-section of seventy countries during the 1990s. At the firm level, though, we do not see any relationship between the firm-level volatility in a country and income per capita.[8] In particular, figure 3.11b illustrates this lack of association between median firm volatility of employment growth and income per capita in a cross-section of fifty-seven countries. This result holds whether or not we aggregate firm volatilities at the country level using the mean or the median.

Finally, we wish to explore the relationship between aggregate and firm-level volatility in the cross-section of countries. Figure 3.12a plots the scatter plot for our sample of fifty-eight countries, which includes both developed and developing economies. It is clear from this figure that when we look at all the countries in the COMPUSTAT GLOBAL there is no relationship between aggregate and firm-level volatility. However, this may be the result of the noisiness of the data for some low income countries.

To mitigate this problem, we explore the subsample of twenty-eight OECD economies. Figure 3.12b contains the scatter plot of aggregate and firm volatility for each of our cross-section of OECD economies during the 1990s. There we can observe a statistically significant negative relationship between aggregate and firm volatility. Interestingly, this negative relationship between aggregate and firm volatility remains significant after controlling for the log of income per capita, the

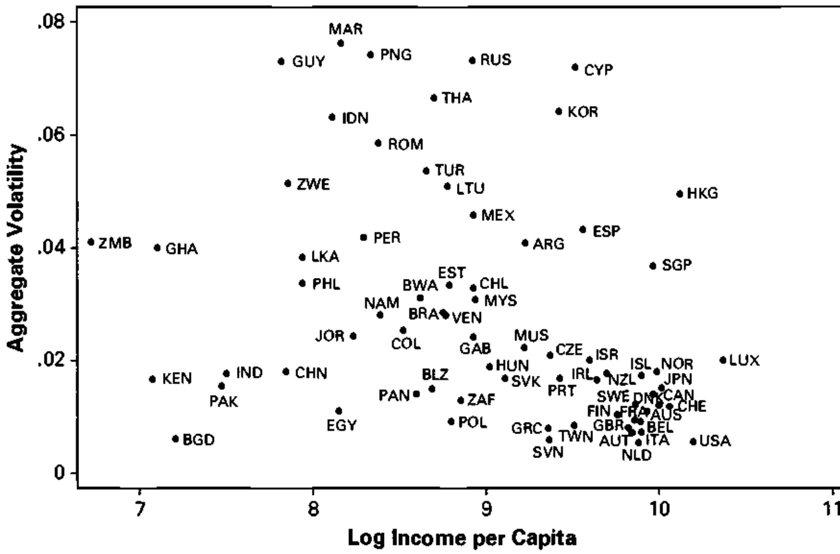

Figure 3.11a
Aggregate Volatility in a Cross-Section of Countries

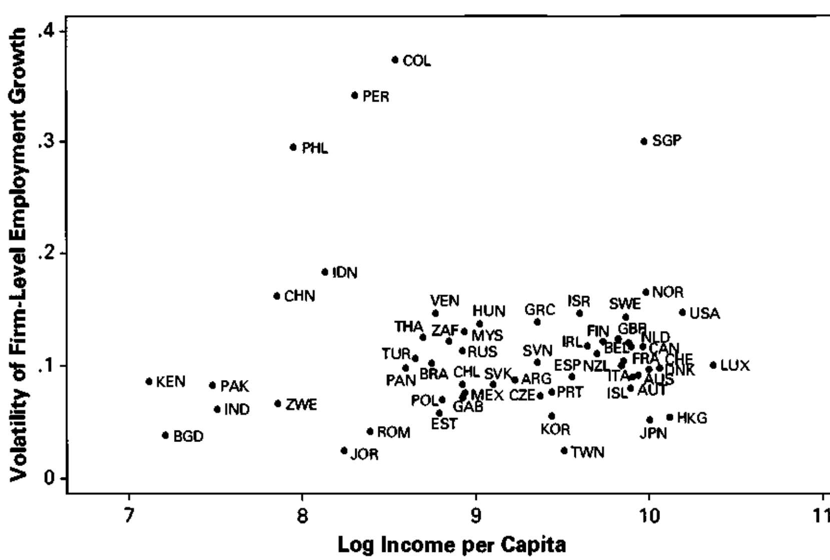

Figure 3.11b
Firm-Level Volatility in a Cross-Section of Countries

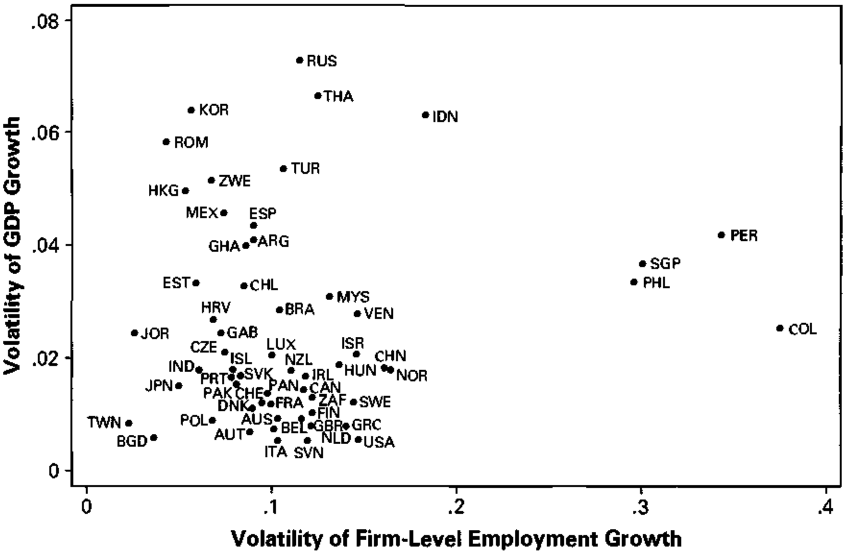

Figure 3.12a
Aggregate and Firm Volatility: Cross-Section of Countries

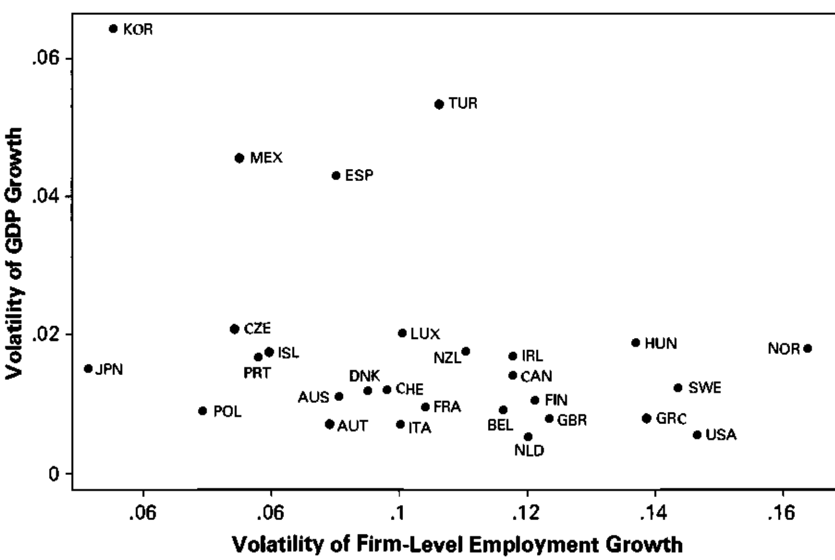

Figure 3.12b
Aggregate and Firm Volatility: Cross-Section of OECD Countries

log average size of firms in a country, or the log number of firms in a country.

We do not want to push too far this relationship between aggregate and firm volatility in the cross-section of OECD countries, but in any case, it supports the conclusions we have drawn previously while exploring the postwar panel of U.S. sectors: namely, that there seems to exist a negative correlation between the evolution of aggregate and firm-level volatilities.

Conclusion 5: Aggregate volatility and income per capita are negatively related across countries.

Conclusion 6: Firm volatility and income per capita are uncorrelated across countries.

Conclusion 7: Firm and aggregate volatility are negatively related among OECD countries.

5 Theoretical Discussion

We are now going to discuss a few possible explanations for the facts that we have uncovered so far. In the last part of the paper, we will try to test these explanations. On the link between sectoral diversification, volatility, and growth, see Acemoglu and Zilibotti (1997), Imbs and Wacziarg (2004), and Koren and Tenreyro (2004).

The first potential explanation is that aggregate stabilization led to more risk taking by firms. The cause of the aggregate stabilization could be luck or better monetary policy. The link with individual risk taking could be the following. Suppose that reallocation is inefficiently low in recessions. Then entrepreneurs may be reluctant to start risky ventures because of the eventuality that they fail at a time where the economy is in a bust. This applies equally to human capital (unemployment risk) or physical capital (fire sales). A decline in aggregate volatility could therefore lead to more individual risk taking.

Other explanations assume that there is a change at the firm level that drives the increase in firm volatility and leads, directly or indirectly, to a decrease in aggregate volatility. Some of these explanations start from an increase in competition in the goods market. It is easy to see how competition can drive up firm-level risk. The explanations differ in how they link competition to aggregate volatility. One explanation, formalized in Philippon (2003), is that more competition leads firms to adjust their prices faster, which reduces the impact of aggregate demand shocks. While intuitively appealing, the simple sticky price explanation cannot be complete because it also implies more volatile inflation, which is contrary to the evidence.[9]

The third explanation, formalized in Comin and Mulani (2005), is that more competition leads to a decline in the correlation of sectoral TFP shocks. To see why this could be the case, suppose that firms decide how much to invest in the development of two kinds of innovations. Idiosyncratic, R&D innovations are patentable and benefit mostly the innovator. General innovations—such as the mass production system and other organizational innovations, improved process controls, product development, testing practices and preproduction planning, new personnel, and accounting practices—are hard to patent and can potentially affect all the firms in the economy. An increase in R&D leads to market turnover and to a reduction in the value of market leaders. Since the marginal value of general innovations is proportional to the value of market leaders, an increase in R&D leads to a decline in the development of general innovations. As a result, the correlation of TFP growth across sectors declines and so does aggregate volatility.

Finally, financial innovation could explain our facts. Financial innovation can lead to more risk taking (see Arrow 1971, Obstfeld 1994). Financial innovation can also work through the competition channel since financial development favors entry of new competitors. On the other hand, financial innovation could prevent credit crunches, make collateral constraints less binding (Bernanke, Gertler, and Gilchrist 1996) and lead to lower aggregate volatility.

6 Product Market Competition

We have already shown that turnover at the top of industries has significantly increased over time (see figures 3.4 and 3.5). Is competition behind this evolution?

6.1 Profit Margins

Figure 3.13 shows the evolution of profit margins. The profit margin for firm i at time t is defined as:

$$\pi_{it} = \frac{OI_{it}}{S_{it}}$$

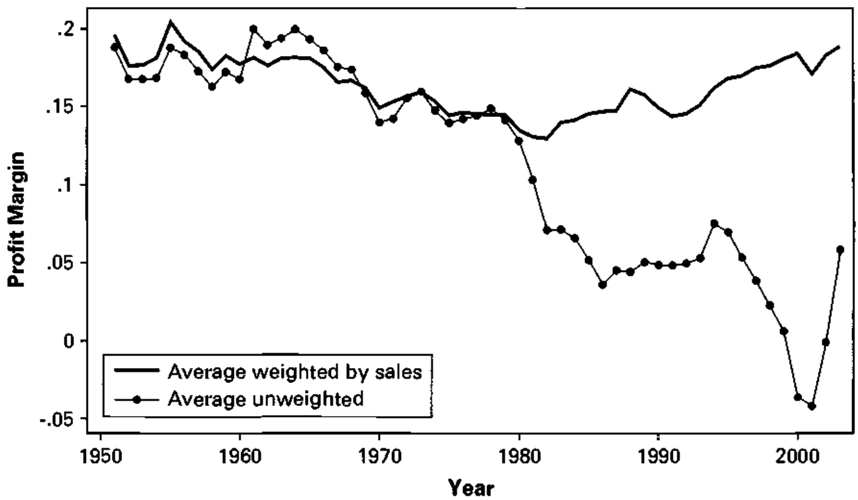

Figure 3.13
Profit Margins: Operating Income over Sales

where OI_{it} is operating income and S_{it} is sales. The key question is how to aggregate profit margins. One way is to take the mean across all firms:

$$\bar{\pi}_{It}^{nonweighted} = mean_{i \in I}(\pi_{it})$$

Another way is to take the sales-weighted average, or equivalently:

$$\bar{\pi}_{It}^{weighted} = \frac{\sum_{i \in I} OI_{it}}{\sum_{i \in I} S_{it}}$$

As figure 3.13 shows, the two measures have had very different evolutions. The stability of the weighted margin means that leaders are as profitable today as they were fifty years ago. However, firms are less likely to remain leaders for very long. The decline of the nonweighted margin is due to the entry of new firms (that often have negative cash flows) and the downfall of previous leaders.

Conclusion 8: Aggregate margins have remained stable because, conditional on being an industry leader, the margins of today are just as high as the margins of yesterday. The key evolution is that firms are less likely to remain leaders now than they were fifty years ago.

6.2 *Evidence from Deregulation*

The results presented in this section follow Irvine and Pontiff (2005), who document that return volatility increases after episodes of deregu-

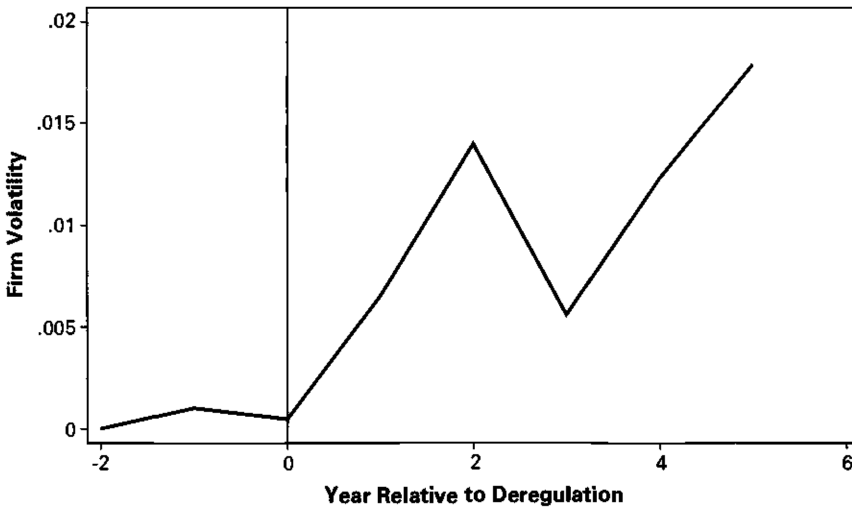

Figure 3.14
Deregulation and Sales Volatility Relative to Nonderegulated Firms
Note: Firm volatility is the standard deviation of sales growth over the past 5 years.

lation. Some industries have been deregulated. For these industries, we can estimate the volatility of firms before and after deregulation, relative to firms in industries that do not experience deregulation. This is a standard difference-in-difference estimation.

For each firm, we define σ_t^i like in equation (2), except that we use only the past five years of data to make the timing more transparent:

$$\sigma_t^i = std.dev(\gamma_{i\tau})_{\tau=t-4...t}$$

We are therefore using a purely backward-looking measure of volatility. For each year, we measure the volatility of firm in industry I against firms in the other industries. The deregulated industries are airlines (1978), entertainment (1984), gas (1978), trucking (1980), banking (1994), railroad (1980), electricity (1978), and telecom (1982). Figure 3.14 shows the evolution of the backward-looking relative volatility measure around the year where deregulation happens. The increase in firm volatility is not very large (about 1.5 percent after five years), but it is statistically significant. In the underlying difference-in-difference regression, the p-value of the test that volatility at $t+5$ is the same as volatility at $t-1$ is 0.0123.

Conclusion 9: Deregulation can account for some of the increase in firm volatility.

Table 3.4
R&D and Firm Volatility, Panel Regression, 1956–1997, Thirty-Five Sectors

	Dependent Variable			
	Mean Volatility of Sales	Mean Volatility of Sales per Worker	Median Volatility of Sales	Median Volatility of Sales per Worker
R&D/sales	3	2.88	0.65	0.49
	(0.93)	(0.83)	(0.29)	(0.21)
N	1,260	1,258	1,260	1,258

Newey-West Standard errors in parentheses. All regressions include a time trend and sector dummies.

7 R&D, Innovations, and Firm Dynamics

Following the Schumpeterian tradition, Comin and Mulani (2005) argue that the observed increase in R&D-driven innovations may be responsible for the increase in the turnover in market leadership and firm volatility. Consistent, with this idea, Chun, Kim, Lee, and Morck (2004) find that firm-specific stock return volatility is higher in industries that invest more in information technology. To explore this hypothesis, we estimate the following regression in a panel of thirty-five two-digit sectors in the United States during the period 1950–2003:

$$\sigma_{s,t} = \alpha_s + \beta t + \gamma RD_{s,t} + \epsilon_{s,t}$$

where σ_{st} denotes the measure of firm-level volatility in sector s at time t, α_s is a sector-specific intercept, and $RD_{s,t}$ denotes total R&D expenses over total sales in sector s during year t.

Table 3.4 reports the estimates of γ for various measures of volatility. In all the cases, there is a positive and statistically significant association between R&D and firm volatility. These estimates are robust to substituting the time trend for time dummies. Further, the estimated coefficient is economically significant. R&D intensity has increased by about 2 percent since the mid 1950s. This implies that the increase in R&D could account for an increase in firm volatility of between 1.5 and 6 percentage points of the total increase of approximately 10 percentage points.

Of course, there is a long way between correlation and causation. Further, the reserve causality argument is particularly plausible in this

Table 3.5
R&D and Firm Volatility, Cross-Section of Thirty-Five Sectors Before and After 1980

	Dependent Variable, Mean After 1980			
	Mean Volatility of Sales	Mean Volatility of Sales per Worker	Median Volatility of Sales	Median Volatility of Sales per Worker
Firm volatility before 1980	1 (.14)	1.1 (0.2)	0.94 (0.12)	1.01 (0.13)
R&D/sales before 1980	5.26 (2.27)	5.96 (2.15)	1.98 (1)	1.35 (0.88)
N	35	35	35	35

context: namely, when it is easier to take over market leaders, and therefore there is more firm volatility, firms have more incentives to invest in R&D to materialize this possibility.

One crude way to check whether R&D has a positive effect on firm volatility consists of exploring whether the increase in firm volatility after 1980 has been larger in the sectors that invested more heavily in R&D before 1980. This is the motivation for the following specification:

$$\bar{\sigma}_{s,POST} = \alpha + \beta\bar{\sigma}_{s,PRE} + \gamma\overline{RD}_{s,PRE} + \varepsilon_s \tag{3.4}$$

By fixing R&D prior to 1980, we avoid the reverse effect of volatility on R&D. In this specification, this comes at the cost of reducing the initial panel to a cross-section of increments in volatility. Table 3.5 reports the estimates for γ in equation (4) for various measures of firm volatility. For all of them, there is a positive effect of pre-1980 R&D intensity on post-1980 firm volatility. This effect is statistically significant at conventional levels for the mean of the volatility of sales and sales per worker and for the median of the volatility of sales. For the median volatility of sales per worker, the effect of R&D before 1980 on firm volatility after 1980 becomes significant if we restrict to the nonprimary economy.

To increase our understanding of the interaction between firm volatility and R&D, we proceed to estimate the following equation:

$$\sigma_{st} = \alpha_s + \beta t + \gamma(j)RD_{s,t-j} + \epsilon_{st}$$

for values of j between 10 and -10. For concreteness, we focus now on the median volatility of sales per worker as a measure of σ_{st}, though the results are very robust to the other volatility measures. Figure

Figure 3.15a
Effect of R&D at $t - j$ on Firm Volatility at t

3.15a reports the estimate of γ for various lags (j), and figure 3.15b reports the associated p-values (in an inverse scale) after computing Newey-West standard errors. In these figures, the lead-lag relationship between R&D and volatility is very clear. As we suspected, current volatility has a significant impact on future R&D that peaks at approximately $t + 3$. However, there is a very apparent effect of past R&D on current volatility that peaks at $t - 5$. This effect is always positive, statistically significant, and typically larger than the contemporaneous correlation between R&D and firm volatility.

Finally, since R&D seems to be an important determinant of firm volatility, we can explore how R&D affects the comovement of sectoral growth. To this end, we estimate the following equation:

$$Corr_{s,t}^{sec} = \alpha_s + \beta t + \gamma RD_{s,t} + \epsilon_{st}$$

where $Corr_{s,t}^{sec}$ is defined in expression (3). The estimates of γ when $Corr_{s,t}^{sec}$ is measured by the correlations of productivity and TFP growth are -3 and -2.4, respectively, with p-values of 2 percent. Hence, the increase in R&D is associated with a decline of between 5 and 6 percentage points in the sectoral correlation of TFP or productivity growth of the observed decline of between 10 and 25 percentage points. These estimates are robust to replacing the time trend by time dummies.

Conclusion 10: Increases in R&D intensity are correlated with significant increases in firm volatility.

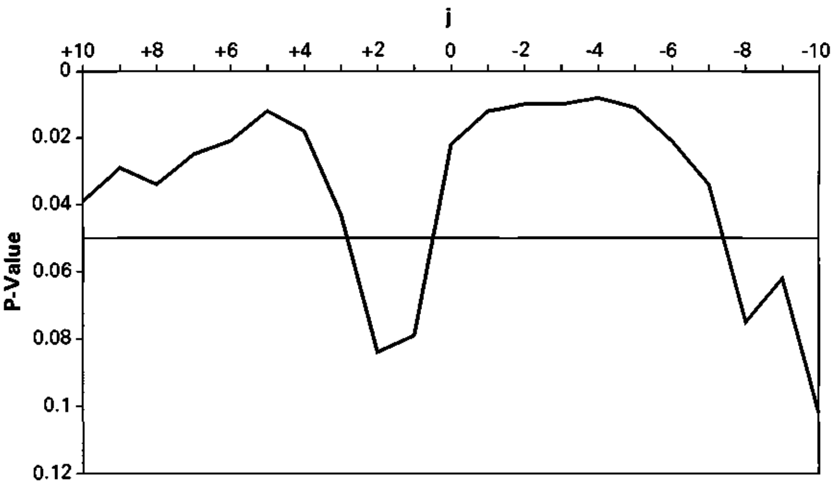

Figure 3.15b
p-Value of the Effect of R&D at $t - j$ on Firm Volatility at t

Conclusion 11: Growth in sectors with larger increases in R&D spending has become less synchronized with aggregate growth in the economy.

8 Financial Development

Before the Great Depression, financial markets for high-risk companies were very active. Corporate defaults were common, and IPOs were numerous (see above for defaults; see Jovanovic and Rousseau [2001] for IPOs). In the 1950s and 1960s, defaults were extremely rare, and IPOs almost disappeared. The high-yield market was reinvented in the 1970s, and IPOs reached historical highs in the 1990s. Li, Morck, Yang, and Yeung (2004) find that firm-specific volatility is linked to the openness of capital markets across emerging countries, but not to openness to trade. Thesmar and Thoenig (2004) find that, among French firms, volatility increased more for publicly traded companies following financial deregulation.

On the macroeconomic side, there are many models and a lot of evidence to support the idea that financial development can reduce aggregate volatility. Recently, Campello (2003) finds that industry markups are more countercyclical when leverage ratios are high, and Braun and Larrain (2004) show that industries that rely more on external finance are more sensitive to aggregate shocks and that the effect is stronger in countries that are less financially developed.

We were not able to find a plausible instrument for financial development, so we can only present reduced form regressions. We want to learn if industries that use a lot of external finance also experience large increases in firm volatility:

$$\sigma_{s,t} = \alpha_s + \beta t + \gamma^{RD} RD_{s,t} + \gamma^{EQ} EQ_{s,t} + \gamma^{LD} LD_{s,t} + \epsilon_{s,t}$$

For sector s at time t, $EQ_{s,t}$ is the ratio of total issues of common and preferred stocks over total sales, and $LD_{s,t}$ is the ratio of total long-term debt issues over total sales. As before, $\sigma_{s,t}$ is the median firm volatility, measured between $t-4$ and $t+5$, and $RD_{s,t}$ is total R&D expenditures over total sales. We obtain the following results for our sample of thirty-five sectors between 1952 and 2002:

	γ^{RD}	γ^{EQ}	γ^{LD}
Coefficient	.974	.267	.106
Standard error	.125	.070	.024

Conclusion 12: Increases in firm volatility are associated with significant increases in R&D intensity and with significant increases in debt and equity issuances.

We can also look at the link between external finance and sectoral correlations (using the correlation of the growth rate of TFP in sector s at time t with the aggregate TFP growth of the economy):

$$Corr^{sec}_{s,t} = \alpha_s + \beta t + \gamma^{RD} RD_{s,t} + \gamma^{EQ} EQ_{s,t} + \gamma^{LD} LD_{s,t} + \epsilon_{st}$$

and we find:

	γ^{RD}	γ^{EQ}	γ^{LD}
Coefficient	−1.93	.256	.109
Standard error	.619	.322	.102

The negative link between TFP comovement and R&D appears robust, but there is no significant link with external financing.

Conclusion 13: R&D intensity is associated with decreases in comovement, while external financing is not.

9 Conclusion

We document a widespread increase in firm-level volatility, which we argue is primarily due to more competition in product markets. We show that competition is best viewed as an increase in the turnover of market shares, as opposed to the more traditional approach emphasizing average markups, or indexes of concentration. We find that average industry profit margins have been roughly stable over the past fifty years because, at any point in time, industry leaders account for most of the sales, and the profit margins conditional on being a leader have not changed much. However, we show that the expected length of leadership by any particular firm has declined dramatically.

We then explore the possible causes for the increase in competition, and we find several explanations. First, we show that firm volatility increases after deregulation. Second, volatility increases more in industries that experience larger increases in R&D investment and in industries that issue more debt and equity.

The contrast between the decline in aggregate risk and the increase in idiosyncratic firm volatility is striking, and we present evidence that the two trends are related. Stock and Watson (2002) show that most of the decline in volatility is due to smaller shocks. We bring two new pieces to the puzzle. First, we show that the decline in the volatility of aggregate shocks is primarily due to a decrease in the correlation of shocks across sectors rather than a decline in sectoral volatility. Second, we show that the correlation of a particular sector with the rest of the economy declines more when firm volatility within this sector increases more. Therefore, we claim that there is a *negative* relationship between firm and aggregate volatility.

Several theories can help us understand this connection, and we classify them in two broad categories. The first group takes the aggregate shocks as given and emphasizes a decline in a particular amplification mechanism, like the credit multiplier or nominal rigidities. We do not find supporting evidence for a role of the investment-financial multiplier in the decline in aggregate volatility. Our data does not allow us to explore the role of nominal rigidities. The second group of explanations argues that competition can lead to a reduction in the correlation of TFP shocks across sectors. We find evidence supportive of this hypothesis: R&D spending at the industry level predicts both an increase in firm volatility within the industry and a decrease in the comovement of the industry with the rest of the economy.

10 Appendix

In this appendix, we derive the decomposition of the variance of aggregate growth into the variance of sectoral growth and the covariance of growth across sectors. The growth rate of the aggregate variable of interest (γ_t) is related to sectoral growth ($\gamma_{s,t}$) as follows:

$$\gamma_t = \sum_s \omega_s^{\sec} \gamma_{s,t}$$

where $\omega_{s,t}^{\sec}$ are the relevant sectoral weights. Aggregate variance of γ_τ between $\tau = t-4$ and $\tau = t+5$ can the be expressed as:

$$V([\gamma_\tau]_{t-4}^{t+5}) = \frac{1}{10}\sum_{\tau=t-4}^{t+5}\left(\sum_s \gamma_{s,\tau}\omega_s^{\sec} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\sum_s \gamma_{s,\tau}\omega_s^{\sec}\right)^2$$

Imposing the restriction that sectoral weights are constant during the interval $[t-4, t+5]$, we can express aggregate variance as:

$$V([\gamma_\tau]_{t-4}^{t+5}) = \frac{1}{10}\sum_{\tau=t-4}^{t+5}\left(\sum_s \omega_s^{\sec}\left(\gamma_{s,\tau} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\gamma_{s,\tau}\right)\right)^2$$

Expanding and manipulating, we obtain the variance-covariance decomposition:

$$\begin{aligned}
&V([\gamma_\tau]_{t-4}^{t+5}) \\
&= \frac{1}{10}\sum_{\tau=t-4}^{t+5}\left(\sum_s\sum_j \omega_s^{\sec}\omega_j^{\sec}\left(\gamma_{s,\tau} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\gamma_{s,\tau}\right)\left(\gamma_{j,\tau} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\gamma_{j,\tau}\right)\right) \\
&= \sum_s\sum_j \omega_s^{\sec}\omega_j^{\sec}\left(\frac{1}{10}\sum_{\tau=t-4}^{t+5}\left(\gamma_{s,\tau} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\gamma_{s,\tau}\right)\left(\gamma_{j,\tau} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\gamma_{j,\tau}\right)\right) \\
&= \underbrace{\sum_s (\omega_s^{\sec})^2 V([\gamma_{s,\tau}]_{t-4}^{t+5})}_{\text{Variance Component}} + \underbrace{\sum_s\sum_{j\neq s}\omega_s^{\sec}\omega_j^{\sec}\, Cov([\gamma_{s,\tau}]_{t-4}^{t+5}, [\gamma_{j,\tau}]_{t-4}^{t+5})}_{\text{Covariance Component}}
\end{aligned}$$

Endnotes

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1. We have checked the robustness of our findings using Bureau of Labor Statistics (BLS) sectoral data.

2. Another way to measure firm volatility is to estimate an autoregressive process and compute the volatility of the innovations. The increase in volatility is the same if we measure it in that way.

3. For a decomposition of firm dynamics into permanent and transitory shocks, see Franco and Philippon (2004).

4. Comin and Mulani (2003) also allow for cohort-specific age and size effects and for autocorrelated errors.

5. This is not to say that M&As are not important. They do not matter much here because we use the median to aggregate across firms. If we had used the mean as our benchmark for figure 3.1, then some large mergers would have affected our measure, and removing these mergers would have made a difference.

6. All of our results also hold using BLS manufacturing data.

7. See the appendix for the derivation details.

8. This lack of association between firm-level volatility and income per capita persist if we compute firm volatility after filtering firm growth from shocks to aggregate growth. Specifically, we regress firm growth on country-time specific dummies and compute the standard deviation of the residuals to measure firm volatility.

9. This is because the standard sticky price model assumes a constant velocity, hence $y = m - p$, and for a given volatility of m, the only way to decrease the volatility of y is to increase the volatility of p. Sticky price models are one example in the class of models with countercyclical markups. Models with real countercyclical markups would not make the counterfactual prediction.

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Comment

Daron Acemoglu, MIT and NBER

Introduction

Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), Stock and Watson (2002), and Boivin and Giannoni (2003), among others, have documented a significant decline in aggregate volatility in the United States and other OECD economies. There is no consensus, however, on the causes of this decline, so many questions regarding its implications and welfare consequences remain unanswered.

On the basis of the aggregate pattern, it would be natural to conjecture that there must have been a similar decline in volatility at the firm level. Nevertheless, such a conjecture need not be right. This can be seen from the following relationship:

$$Var\left(\sum_{i}^{n} \alpha_i x_i\right) = \sum_{i}^{n} \alpha_i^2 \; Var(x_i) + 2\sum_{j>i}^{n} \alpha_i \alpha_j \; Cov(x_i, x_j) \tag{1}$$

where, in this context, $x = \sum_i^n \alpha_i x_i$ is the growth rate of aggregate output, x_i is the growth rate of value added of firm i, and α_i is the share of value added of firm i in aggregate output, with $\sum_i^n \alpha_i = 1$. This equation implies that a decline in the variance of aggregate output x does not necessarily imply that $Var(x_i)$'s or their (weighted) averages have declined. Instead, the decline in aggregate variance may result from a reduction in comovement (a decline in the covariance terms) or from increased diversification (the economy may have added another firm or sector, so that n has increased).

Therefore, understanding how firm-level volatility has changed over the past thirty years would be very informative for understanding why aggregate volatility has declined. Some theories of declining volatility at the aggregate level, such as those emphasizing the improved conduct of monetary policy, would naturally suggest that we should expect similar changes at the firm level, whereas others, for example, those emphasizing structural change, could be more consistent with reductions in comovements across sectors and firms.

A number of recent papers have started investigating changes in firm-level volatility. Perhaps surprisingly, the picture that emerges is one of increasing firm-level volatility going hand in hand with declining aggregate volatility.

The paper by Comin and Philippon surveys some of the recent findings and adds to them. It is clearly written and makes a good case that firm-level volatility has been increasing. It has convinced me that we have to take the pattern of increasing firm-level volatility seriously and understand its theoretical underpinnings.

However, the authors do not develop the theoretical implications of their findings fully. Although many different theories, some of them mentioned by the authors, are consistent with certain patterns in the data, it would be interesting to start from a fully-specified model and look at the data through the lenses of such a model. What do these patterns mean? Can some of the existing theories do a good job of accounting for the patterns?

I will start with a brief discussion of the empirical patterns presented by the authors and their robustness, and then work through a simple model based on my previous work (Acemoglu and Zilibotti 1997) to present a possible interpretation for the findings. This is not meant to argue that this model is the right explanation, but it is intended to illustrate that we need models to interpret these facts. Other models, more tightly tailored to the questions related to aggregate volatility and the facts presented here, may do a better job.

Empirical Patterns

Basic Facts

I will start with the facts that appear to me to be more important. These are:

1. Firm-level volatility has increased *steadily* over the past fifty years.
2. There is a similar picture emerging from idiosyncratic risk of firm returns.

3. There is now less comovement of different sectors; i.e., *covariance terms in equation (1) above have declined.*

4. Aggregate volatility and income per capita are negatively related across countries.

5. The evidence on the relationship between firm volatility and income per capita seems to be inconclusive.

I have emphasized the steadiness of the increase in firm-level volatility since I believe this should be an important ingredient in our thinking. For similar reasons, I also emphasized the decline in covariance.

Comin and Philippon discuss a number of other facts in their paper. Since my purpose here is to interpret the patterns related to firm-level volatility (and its relationship with aggregate volatility) through the lenses of a simple model, I have chosen to focus on these to start. After all, theories are useful in part because they guide us in our choice of which facts to focus on.

Even when we focus on a subset of facts presented in this paper, the implications are remarkable. If these facts are robust, they are important ingredients (and challenges) to theories of aggregate volatility.

Robustness

Are the facts robust? Comin and Philippon provide a number of robustness checks, and Campbell et al. (2001) provide more robustness checks on the pattern of equity returns. I am largely convinced by these patterns and believe that we have to take the increase in firm-level volatility seriously. Nevertheless, there are two areas in which more checks would be useful.

1. Are the results an artifact of the sample used by the authors?

Here, the concern is that the sample is that of listed firms, so one may worry about whether firms that *become* listed in the recent past are more risky. The authors show results that control for age and size, but more can be done here. For example, one should look at how volatility of a *cohort* of firms changes relative to the changes of a same-age cohort of firms in the past. This would be similar to the exercises in the inequality literature (e.g., Juhn, Murphy, and Pierce 1993), which tried to control for cohort-specific factors in accounting for the rise in overall inequality in the United States.[1]

Similarly, as an alternative control for sample selection, one should look at how the results change when the analysis is conducted on the subset of firms that have been continuously listed since 1960.

2. Is there supporting evidence from other sources?

If firm-level volatility is increasing, we should see this in other data sets as well. For example, there should be more "churning," for example, greater expansions and contractions of firms. Is there any evidence of this?

As a quick check, we can look at the job reallocation data in the manufacturing sector from Davis, Haltiwanger, and Schuh (1996). These data give us one measure of volatility at the plant-level for the manufacturing sector. Interestingly, they do not show any increase in job reallocation, so at the very least, one should try to reconcile the increase in the volatility of listed firms in this study with the job reallocation data.

Comin and Philippon's Explanations

Comin and Philippon suggest a number of explanations for this pattern. However, they do not investigate these in detail, and it is not clear whether they can account for the most salient patterns in the data (and whether they are theoretically compelling).

Here I briefly discuss their suggested explanations. I place special emphasis on the fact that a parsimonious theory should account both for the firm-level and aggregate patterns, and judge the theories against this benchmark.

Increased Competition

Comin and Philippon provide suggestive evidence that increased product market competition (perhaps driven by deregulation) may have contributed to increased firm-level volatility. Most important, they document that there is more turnover in the ranks of firms (especially in the positions of market leadership), and there has been greater increase in volatility in sectors undergoing deregulation.

Though interesting, this evidence is not necessarily conclusive, since the usual worries associated with any correlation-type evidence apply; deregulation and its timing could be endogenous, and other factors about the deregulated industries could be driving the increase in volatility.

My most important problem with this explanation is different, however. As emphasized above, the increase in firm-level volatility appears to be a relatively steady phenomenon rather than a trend confined to the aftermath of deregulation only. It is therefore difficult to imagine that deregulation itself is at the root of the patterns we observe.

Having said that, it would have still been interesting to dig deeper into explanations related to changes in the level of competition in the product market. A theory of increased volatility at the firm level due to deregulation does not necessarily predict a decline in aggregate volatility. If something else—in particular, the covariances—does not change, then aggregate volatility will also increase. So why do we have a decline in aggregate volatility? One avenue investigated by Phillippon (2003) is the possibility that greater competition leads to more frequent price adjustments and reduces aggregate volatility via this channel. Another possibility would be to investigate potential changes in market structure that can simultaneously account for the greater turnover in leadership positions and the relative stability of average industry profit margins. It would be nice to see the authors investigate this more.

Increased R&D-Based Competition

Another hypothesis that the authors suggest is that increased R&D-based competition is responsible for increased firm-level volatility. Their main theoretical idea is this: R&D, especially new product or technology development, is a risky activity. Therefore, perhaps increased R&D-based competition will increase firm-level volatility. Nevertheless, it is unclear why R&D-based competition should reduce aggregate volatility and also whether greater R&D necessarily means greater R&D-based competition (as opposed to greater R&D creating a shield for incumbents and reducing competitive pressures).

Having said that, I again believe that one can develop an interesting theory where a patent-race (e.g., Harris and Vickers 1987) reduces the covariance between firms. Another interesting angle might be to consider a shift from imitation-based to innovation-based growth (e.g., Acemoglu, Aghion, and Zilibotti 2003) and investigate whether such a shift could have a systematic effect on the relationship between aggregate and firm-level volatility. But the authors do not go down this route and do not present a worked-out model.

Instead, they provide evidence that increases in R&D intensity at the sectoral level are correlated with increases in volatility at the firm level. But it is difficult to know what to do with this evidence. First of all, omitted characteristics of firms and sectors are potentially correlated with other determinants of volatility. Second, many other theories, based on different driving forces, might imply this pattern as a consequence of the change in the level and distribution of sales across firms.

The other issue that comes up again is the steady nature of the increase in firm-level volatility. At face value, this story would have a chance only if the increase in R&D-based competition were a steady phenomenon, but it is not clear whether or not this is so, and the paper does not get into these issues.

A Model: Diversification and Financial Development

Comin and Philippon also mention financial development as another potential explanation but do not make much of it. Perhaps because I have worked on such models, I believe that general equilibrium models of financial development, risk-taking, and risk-diversification provide a particularly useful perspective for thinking about the relationship between firm-level volatility and aggregate volatility. Both to highlight the implications of such models and to emphasize the usefulness of looking at the facts through the lenses of a theory, I now present a bare-bones version of a model based on Acemoglu and Zilibotti (1997).

Model

Fabrizio Zilibotti and I analyzed a general equilibrium model of risk-taking and diversification to investigate how aggregate volatility and productivity change over the process of development and the role of shocks in takeoff. This model was not designed to think about firm-level volatility. Here I present a variant of that model with two differences:

1. Aspects related to capital accumulation are stripped away to simplify the exposition.
2. I pay special attention to firm-level volatility to generate insights about the facts that are on the table here.

Also, because of space constraints, I will not give all the details and derivations, which are very similar to those in Acemoglu and Zilibotti (1997).

There is a continuum of equally likely states represented by the unit interval. There is also a potential for $1/\epsilon$ of firms (where $\epsilon \to 0$), depending on resources and available technology. Firm $j \in [0, 1]$ covers an interval of length ϵ over the unit interval disjoint from those of other firms. It has access to the following technology of production:

$$y_t^j = r\phi_t^j + \theta_t^j \frac{R}{\epsilon}(\epsilon F_t^j)$$

$$= r\phi_t^j + \theta_t^j R F_t^j \tag{2}$$

where $R > r$, and $\epsilon F_t^j + \phi_t^j$ is the total amount invested in this firm, with ϕ_t^j invested in safe activities with a rate of return r, and ϵF_t^j invested in risky activities with a rate of return R/ϵ. The variable θ_t^j is defined such that $\theta_t^j = 1$ if the realization of a uniform random variable over the unit interval falls in the ϵ interval controlled by this firm. This implies that $\text{Prob}[\theta_t^j = 1] = \epsilon$ and also that a balanced portfolio of $1/\epsilon$ firms, each with $\phi_t^j = 0$, will have a rate of return of R for sure. This is a convenient feature of this specification since the number of firms will directly correspond to diversification. As $\epsilon \to 0$, each firm pays out in a single state and so is similar to a basic Arrow security, and we use j both to denote the underlying state and the corresponding firm paying out in that state. Another important feature of equation (2) is that a greater ϵF_t^j relative to ϕ_t^j implies that the output of the firm will be more risky (i.e., there will be more risk-taking at the firm level).

On the technology side, there are two types of constraints on the number of active firms:

1. Minimum size requirements.
2. Available technology.

These constraints are important since otherwise, the economy (and all consumers) would choose a balanced investment in all firms without any risks. Limits on the resources available to the representative consumer and technology will prevent this riskless allocation and introduce a trade-off between risk and return. More specifically, minimum size requirements refer to the fact that risky investment in firm j cannot be less than a certain amount $M(j)$; i.e., we need $F^j \geq M(j)$ for some $M(j) \geq 0$. To keep the analysis tractable let us assume:

$$M(j) = \max\left\{0, \frac{D}{(1-\gamma)}(j-\gamma)\right\}$$

where firms are ranked in increasing minimum size. This formulation means that the first γ sectors do not have minimum size requirements, and that minimum size requirements increase linearly. In addition, at time t the available technology dictates that only firms with $j \leq \bar{n}_t$ can be active.

Let us also assume that the economy admits a representative consumer with logarithmic preferences and that a total amount of K_t can be invested at time t. To characterize the equilibrium, we need to be more specific about the market structure and the concept of equilibrium. Let us assume that there is free entry at the beginning of the period and that a large number of agents without any funds can enter and operate each potential firm (without any further costs). If they decide to operate a firm, they need to raise all of the investment of the firm from the consumers by selling claims to their output. Given this, we define an equilibrium as an allocation such that, given the set of active firms, prices clear all markets, and the set of active firms is determined by free entry.[2]

To characterize the equilibrium, let J_t be the set of active firms. Given the set of active firms, the equilibrium is competitive, so it will be a solution to:

$$\max_{\{\phi_t^j\}_{0\le j\le 1},\{F_t^j\}_{0\le j\le 1}} \int_0^1 \log(c_t^j)\,dj \tag{3}$$

subject to:

$$\int_0^1 \phi_t^j\,dj + \int_0^1 F_t^j\,dj = K_t \tag{4}$$

$$c_t^j = r\int_0^1 \phi_t^j\,dj + RF_t^j \tag{5}$$

$$\phi_t^j = F_t^j = 0 \qquad \forall j \notin J_t \tag{6}$$

Equation (4) imposes that total investment is equal to total resources, K_t; equation (5) specifies consumption in state j as equal to return on safe assets and investments in the firm paying out in state j; and finally equation (6) imposes that there will be no investment in firms that are not active.

Two features make the characterization of equilibrium simpler. First, lower-ranked firms will be active first in equilibrium (since the returns from all firms are symmetric, but higher-ranked firms are more expensive since they require more resources). Second, the above program implies equal risky investment for all active firms (again since the returns from all firms are symmetric).[3] In view of these observations, we have the following form of the solution; let firms $j \in [0, n_t]$ be the set of active firms, then:

$$\phi(K_t, n_t) \equiv \int_0^1 \phi_t^j \, dj = \frac{(1-n_t)R}{R - rn_t} K_t \tag{7}$$

$$F_t^j = \begin{cases} F(K_t, n_t) \equiv \frac{R-r}{R-rn_t} K_t, & \forall j \leq n_t \\ 0 & \forall j > n_t \end{cases} \tag{8}$$

The most important observation here is that $F(K_t, n_t)$ is increasing in n_t, while $\phi(K_t)$ is decreasing in n_t. This is because as n_t increases, there is greater diversification, so greater investments in risky activities become less costly. The implication is that as n_t increases, the average firm becomes more risky [since their risky investment, $F(K_t, n_t)$, increases, and its safe investment, $\phi(K_t, n_t)$, declines].

How is n_t determined in equilibrium? This is where we turn to the free-entry condition. Suppose that $n_t < \bar{n}_t$. Then as long as one more firm can enter and make positive profits, there will be entry. Imagine that equilibrium n_t were such that $F(K_t, n_t) > M(n_t)$, then one more firm could enter and charge a premium to individuals holding its stock to make positive profits. Also, $F(K_t, n_t) < M(n_t)$ could not be an equilibrium since it would violate feasibility. Therefore, when we are in the region where $n_t < \bar{n}_t$, equilibrium $n^*(K_t)$ must be such that $F(K_t, n^*(K_t)) = M(n^*(K_t))$. Naturally, it could be that we reach $\bar{n}_t$ while still $F(K_t, n_t) > M(n_t)$, and further entry is not possible because of this technological restriction. Therefore, the equilibrium number of firms in the economy is given by:

$$n_t = \min\{n^*(K_t), \bar{n}_t\}$$

Implications

We can now discuss the implications of this simple model.

1. Increases in n_t, which we can associate with the level of development of the economy, lead to increasing risk-taking by firms. Therefore, if n_t is increasing over time, we should see greater risk-taking by firms.

2. Equilibrium n_t is not decreasing in K_t and $\bar{n}_t$, so both more resources and technological progress will increase risk-taking by firms. Therefore, this model suggests a secular (steady) pattern of increasing risk-taking by firms.

3. It can also be shown that economy-wide Total Factor Productivity (TFP) is also increasing in n_t since as n_t increases, more resources are allocated to the higher productivity (risky) activities.

4. More important for the focus here, aggregate volatility is also a function of n_t. Let $V(n_t) \equiv Var(c_t)$ be the variance of consumption or income. Thus:

- If $\gamma \geq R/(2R-r)$, then $\partial V(n_t)/\partial n_t \leq 0 \ \forall n_t$
- If $\gamma < R/(2R-r)$, then $\exists n'$ such that

$$\frac{\partial V(n_t)}{\partial n_t} \leq 0 \qquad \forall n_t \geq n'$$

$$\frac{\partial V(n_t)}{\partial n_t} > 0 \qquad \forall n_t < n'$$

This result implies that aggregate volatility could be at first increasing in the extent of development but is eventually decreasing in n_t. This is because of increasing diversification (i.e., decreasing correlation between firms). Combined with implication 1 above this implies that, at least after a certain stage, there will be a simultaneous increase in firm-level volatility and a decline in aggregate volatility.

5. The model also has some immediate implications about financial development. To develop these implications, suppose that there is endogenous participation in this economy. In particular, a unit measure of consumers have capital k each, and an outside option ω_i distributed according to some cumulative density function G. Moreover, taking part in the stock market and investing in firms has a transaction cost τ. Let the maximized value of the above program be $U(\bar{n}_t, K_t)$. If $\omega_i > U(\bar{n}_t, K_t) - \tau$, then individual i does not participate in the stock market and does not invest in firms. This implies that the equilibrium amount of funds invested in firms will satisfy:

$$K_t = G(U(\bar{n}_t, K_t) - \tau)k$$

Inspection of this equation implies that multiple equilibria are possible since greater K_t enables better diversification and increases the utility of participation, leading to greater investments. More important is the fact that when $\bar{n}_t$ increases because of technological progress, this has an *amplified* effect because it induces financial development (i.e., the amount of resources to be invested in firms, K_t, increases). Consequently, financial development induced by a decline in τ leads to an increase in firm-level volatility and a decline in aggregate volatility. This highlights the fact that financial development could be associated with increased risk taking by firms (and reduced aggregate volatility), even though it is itself determined endogenously in equilibrium.

In addition to the results and implications discussed here, there are a number of other results that are useful to mention. First, in Acemoglu and Zilibotti (1997), the equilibrium is not Pareto optimal (because of the pecuniary externalities created by endogenous market incompleteness). Second, this inefficiency disappears as $n_t \rightarrow 1$.[4]

Finally, but also crucially, this model highlights another important theoretical aspect: the internal organization of the firm matters. If two firms merge, firm-level volatility will decline. Therefore, whether firm-level volatility increases over the process of development depends on whether expansion is undertaken by existing firms or by new firms (extensive versus intensive margin). Consequently, theories of the relationship between the firm-level and aggregate volatility have to model the internal organization and boundaries of firms. This seems to be an important and interesting area for future research.

Rethinking the Evidence

Having worked through the model, we can now look at the facts through the lenses of this theory. A number of results are apparent:

- According to this model, there should be a negative relationship between aggregate and firm-level volatility.
- There should also be a negative relationship between income per capita and aggregate volatility (and a positive relationship with the firm-level volatility).
- There should be a steady increase in firm-level volatility and a steady decline in aggregate volatility.
- The model highlights that the driving force can be technological or related to financial development.
- Organization of firms and sectors matters for the relationship between aggregate and firm-level volatility.

Consequently, despite its simplicity, this existing model appears to be consistent with the salient patterns emphasized by Comin and Philippon.[5] This does not imply that it is the right explanation, and a more-in-depth analysis might reveal that it has qualitative or quantitative features that do not match the data. Nevertheless, it suggests that theories that endogenize risk diversification and risk-taking provide an interesting avenue for understanding the simultaneous decline in aggregate volatility and increase in firm-level volatility. It also highlights the use of fully worked out models in thinking about these sets of issues.

Conclusion

To conclude, the literature surveyed and the facts presented in this paper are important for our thinking on many topics. They are relatively convincing about an increase in firm-level volatility and that we ought to think about the change in aggregate volatility differently. This is an important achievement, but it will be useful only when we start thinking more systematically about what types of models can be consistent with these facts and what the implications are for aggregate observables and welfare. One interesting issue, already mentioned above, is to think more systematically about whether changes in the boundaries of the firm interact in interesting ways with aggregate volatility.

Endnotes

1. Such an exercise would be useful if, for example, one suspected that there was a relationship between age of firms and firm-level volatility.

2. This is not the same as an Arrow-Debreu equilibrium, which would require all markets, even those in which there is zero transaction, to clear. Because of the endogeneity of the commodity space, a weaker equilibrium concept is more appropriate here. This will also be the reason why the decentralized equilibrium is not necessarily Pareto optimal (see below and also Acemoglu and Zilibotti 1997).

3. The allocation of the total investment in riskless activities, $\int_0^1 \phi_t^j \, dj$, across firms, on the other hand, is indeterminate since firm-level volatility does not matter for consumers.

4. We can also identify F_t^j with R&D-like activities. Therefore, this class of models would be able to account for the correlation between R&D-type activities and sectoral volatility.

5. See Thesmar and Thoenig (2004) for a model along these lines applied to French data.

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Comment

Janice Eberly, Northwestern University and NBER

Diego Comin and Thomas Philippon have written an intriguing paper compiling evidence on the rise in firm-level volatility in the second half of the twentieth century—despite a concurrent decrease in aggregate volatility. This increase in idiosyncratic volatility is evident from many angles: in both real and financial data, across firms and within a firm over time, and across industries. Comin and Philippon parse the data in other ways in order to better understand the source of increasing volatility at the firm level. Before attempting to associate these facts with a theory, however, my comments first focus on solidifying the evidence. The angle I take on the data is largely supportive of the Comin and Philippon findings, though it raises some questions. In particular, it remains to be seen whether the increase in volatility, which was particularly pronounced in the 1990s, will persist into the new millennium. The data raise some questions on this point, and the answers help to delineate between different explanations. Most of the explanations suggested in the paper and in the literature are consistent with a trend or possibly a level increase in firm-level volatility, resulting from an increase in competitiveness or financial development, for example. However, the data suggest a possible reversal in the volatility trend. In that case, we need to explain an episode, not a trend, which gives a different flavor to the proposed explanations.

My comments will begin with the financial data, and then turn to the real data. The financial data give us a slightly different view of the firm and the aggregates since they are available at high frequency and give a measure of market value (rather than current sales). The standard reference in this literature is Campbell, Lettau, Malkiel, and Xu (*Journal of Finance*, 2001, CLMX hereafter), who examine the equity values of publicly traded firms from 1926 through 1997. Looking first at the aggregate index, they find that "there is no discernible trend" (p. 9) in the standard deviation of the value-weighted index returns over this time period.[1] CLMX then decompose the aggregate index into market-wide, industry, and firm-level risk. They find that all three are countercyclical, so that volatility from all sources is higher during recessions. However, the firm-level volatility data show a marked upward trend (CLMX, figure 4), while the market and industry volatilities show no clear, long-run trend (CLMX, figures 2 and 3).

The next angle taken by the literature and the authors is to step away from the public market valuation of firms and directly examine firms' performance—either sales or output. At the aggregate level, several well-known papers have documented a striking decrease in the volatility of aggregate gross domestic product (GDP). McConnell and Perez-Quiroz (2000) and Stock and Watson (2002) both document the declining volatility of aggregate GDP over the postwar period, which McConnell and Perez-Quiroz identify as a structural break in 1984. To check the robustness of these findings, I use data on final sales for 1947 to 2004 and find much the same pattern, as shown in figure 3.16. The four-quarter standard deviation of growth in final sales is 2.1 percent in the full sample, which represents a decline from 2.4 percent in the first half of the sample to 1.7 percent in the second half. (Using 1984 as the break point, the standard deviation of final sales falls from 2.4 percent pre-1984 to 1.3 percent for 1984 and later.)

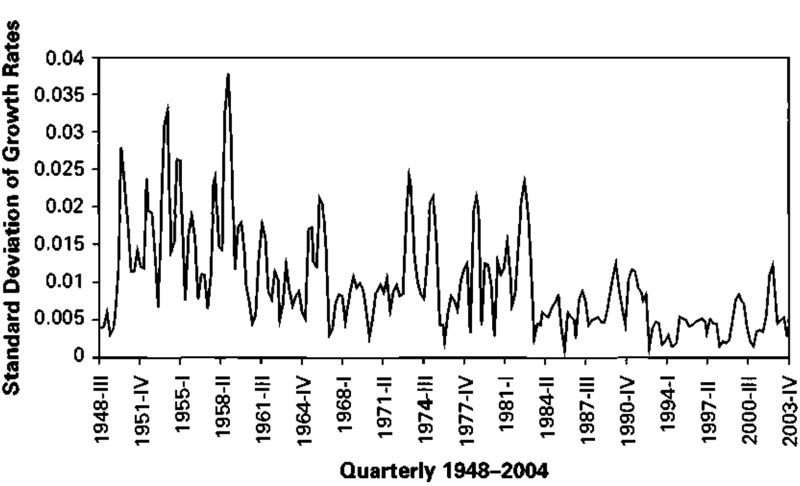

Figure 3.16
Four Quarter Standard Deviation of Growth in Final Sales

The most obvious explanation for such a decline in aggregate volatility is a change in the composition of GDP—toward less volatile service sectors. Indeed, the goods component of GDP has fallen from 80 percent to 60 percent, while services have risen accordingly. A basic calculation suggests, however, that a simple change in composition is not sufficient to explain the reduction in aggregate volatility. Using the volatilities and covariance of goods and services for the full sample and doubling the share of services reduces the aggregate standard deviation by 12 percent, whereas in the data it falls by at least 30 to 40 percent, depending on the exact measure and break point. Thus, composition, or at least the split between goods and services, does not seem sufficient to explain the reduction in aggregate volatility. Directly examining the volatilities of goods and services separately reinforces this view. Figure 3.17 plots the four-quarter standard deviations of final sales of goods and final sales of services. Even within the goods and services categories, there is a substantial decline in volatility. So if composition is to be the explanation, there must be compositional change within goods and within services as well.[2]

This decline in aggregate volatility is in contrast to a trend of increasing volatility at the firm level, which is the centerpiece of the paper. Figure 3.1 in the paper demonstrates this finding graphically, showing

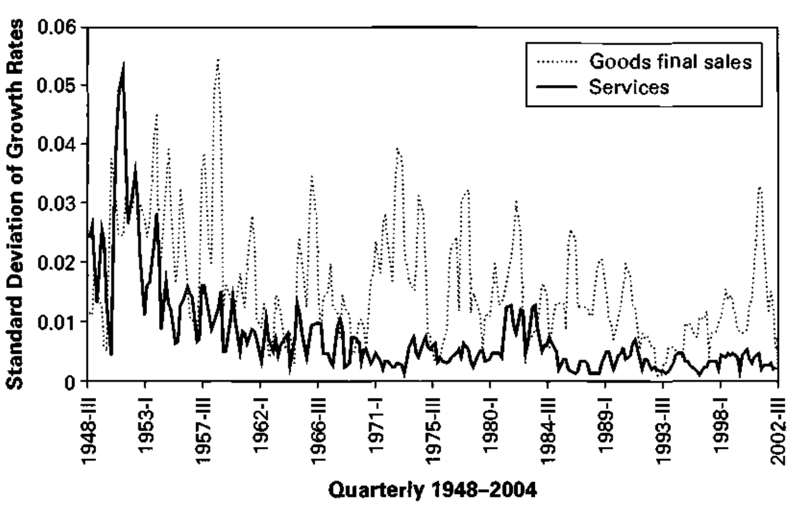

Figure 3.17
Four Quarter Standard Deviation of Growth Rates

that the median volatility of firms has risen from a low of 7.5 percent in 1960 to about 20 percent in 2000. It is worth noting how this is measured. The authors calculate for each firm the growth rate of sales in each year from the COMPUSTAT sample of publicly traded firms. They then calculate a ten-year standard deviation of these growth rates, centered on the current year; more precisely, they include four leads, the concurrent value, and five lags. This gives the standard deviation of sales for a firm in a given year. The authors then calculate the median of this value across firms, and the result is plotted in figure 3.1, while the other quartiles plotted in figure 3.2 show that the phenomenon of rising volatility carries across the distribution of firms.

Again an obvious explanation for this observation is the composition of the sample. The number of publicly traded firms has increased dramatically over time; Fama and French (2001) show that the number of publicly traded non-financial non-utilities increased by a factor of five from 1960 to 2000.[3] Moreover, the new entrants are measurably different than the incumbents; in addition to being younger, they are smaller, less likely to pay dividends, and on average less profitable. Comin and Philippon recognize this difference in composition and control for age and size by regressing each firm's volatility measure on log(age) and size, as well as industry dummies. The residuals show a similar upward trend, as graphed in figure 3.3 of the paper. Using this method to control for possible compositional effects requires that the effects of age, size, and industry are constant over time and across firms, and moreover that they capture the relevant heterogeneity. Campbell, Lettau, Malkiel, and Xu face a similar problem in their equity return data and instead control for compositional effects by creating a balanced panel of incumbent firms, which by construction has a fixed composition.[4] They still find a convincing pattern of rising volatility in this sample; it would be interesting to see if the same result would obtain in the sales data from the COMPUSTAT firms.

The final angle from which to examine these data is the time series. Any measure of volatility necessarily has time dimension, and Comin and Philippon use a ten-year rolling window to calculate each firm's standard deviation of sales growth. Their sample ends in 2004, so the final year of their volatility measure is 2000. The effect of changing the breadth of the window used for calculating volatility is nicely evident in CLMX's figures, where they provide two panels, one graphing the within-month firm volatility and the second graphing a twelve-month moving average. To provide a similar comparison for firm-level sales

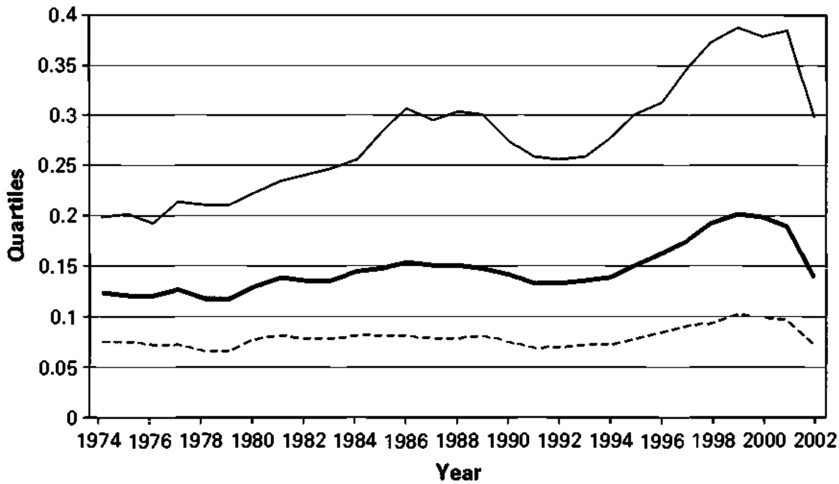

Figure 3.18
Five-Year Centered Standard Deviation of Firm-Level Sales Growth, 1974–2002

growth volatility, I reproduced Comin and Philippon's distributions of sales growth and then varied the window-length for computing the standard deviation. First, using Comin and Philippon's ten-year window, I verify that my sample matches the 25th, 50th, and 75th percentiles reported in figure 3.2 of the paper. In each case, it matches to within one percentage point. Using a five-year window gives a very similar picture, with the median-firm standard deviation rising from 12 percent to 20 percent from 1974 to 2000. However, narrowing the window allows us to extend the sample, in the sense that the last year for which we can estimate a standard deviation is now 2002 instead of 2000. This small adjustment in the calculation, however, can make a large difference in the endpoint, as shown in figure 3.18. The estimated median volatility in 2002 is only 14 percent, which is substantially lower than the 20 percent estimated for 2000 and only slightly higher than the starting point of 12 percent. Figure 3.19 shows the results of using a three-year window to calculate the standard deviation, which smooths the data less but gives a clearer picture of what is happening near the endpoints. In this figure, by 2003, each quartile of the standard deviations returns to its beginning-of-sample value.

These calculations suggest the possibility that the greater volatility evident in firm-level sales may be reversing itself. In particular, the acceleration of volatility observed in the 1990s may have been temporary. Going back to financial data is useful at this point since these

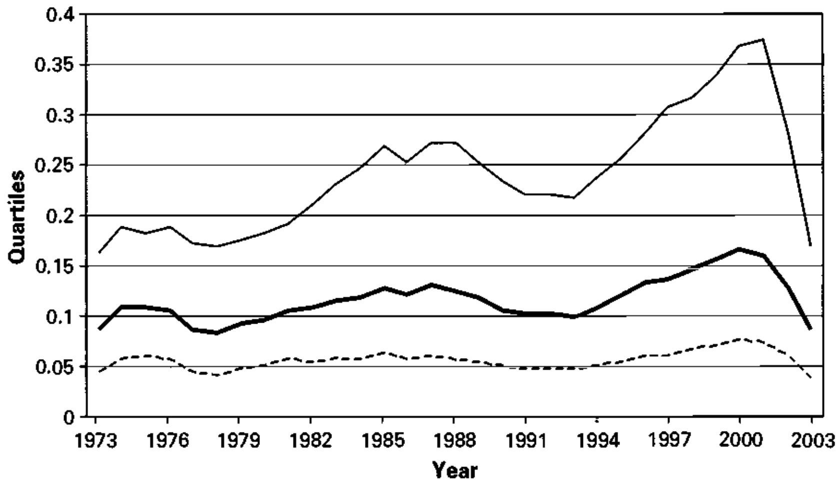

Figure 3.19
Three-Year Centered Standard Deviation of Firm-Level Sales Growth

data are available at high frequency. The Chicago Board Options Exchange (CBOE) publishes implied volatilities on individual stocks, as well as indexes. Figure 3.20 graphs the average and figure 3.21 graphs the quartiles of individual firm volatilities since 2001. The average volatility (standard deviation) has fallen from 88 percent to 30 percent, while the median has fallen from 80 percent to 25 percent from March 2001 to December 2004.[5] The implied volatilities on the indexes have also declined markedly, with the S&P 500 index volatility hovering below 15 percent and the NASDAQ volatility below 20 percent—which is one-half to one-third their levels in 2001 and 2002. This reduction in volatility is not only a characteristic of implied volatilities on options, it is also evident in realized volatilities. Figure 3.22 shows the realized volatilities of several individual stock returns, demonstrating the reversion of volatility to its levels of the early 1990s—following the turbulence of the late 1990s and early 2000s.

While the late 1990s strike many intuitively as a turbulent period, consistent with high firm-level volatility, there is also supporting statistical evidence. The Small Business Administration reports net business creation, as well as births and deaths, since 1989. Figure 3.23 shows the rise in net firm creation in the early 1990s, but then a decline following 1995, which actually leveled off during the recession in 2001. This dampening of net business creation masks enormous turbulence in the

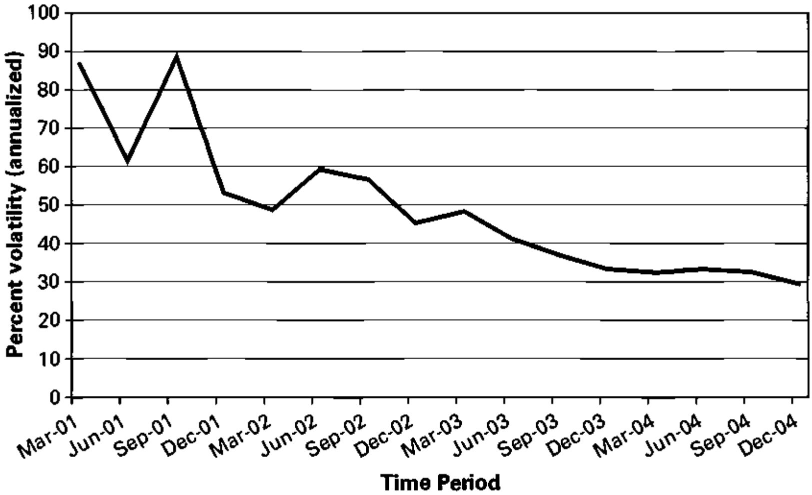

Figure 3.20
Average Firm-Level Volatility

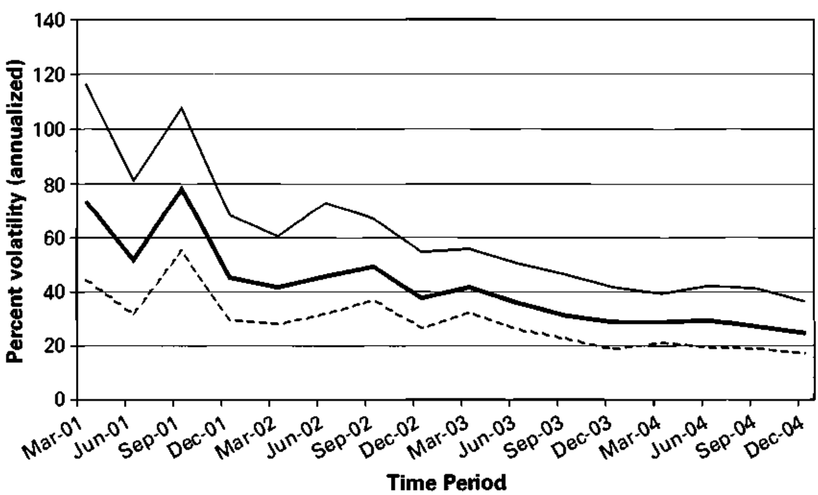

Figure 3.21
Firm-Level Volatility Quartiles

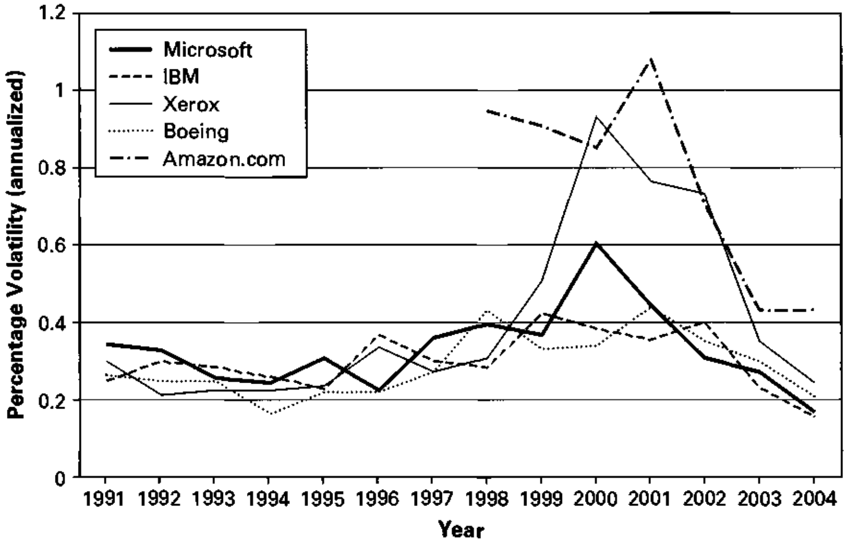

Figure 3.22
Individual Equity Volatility, 1991–2004

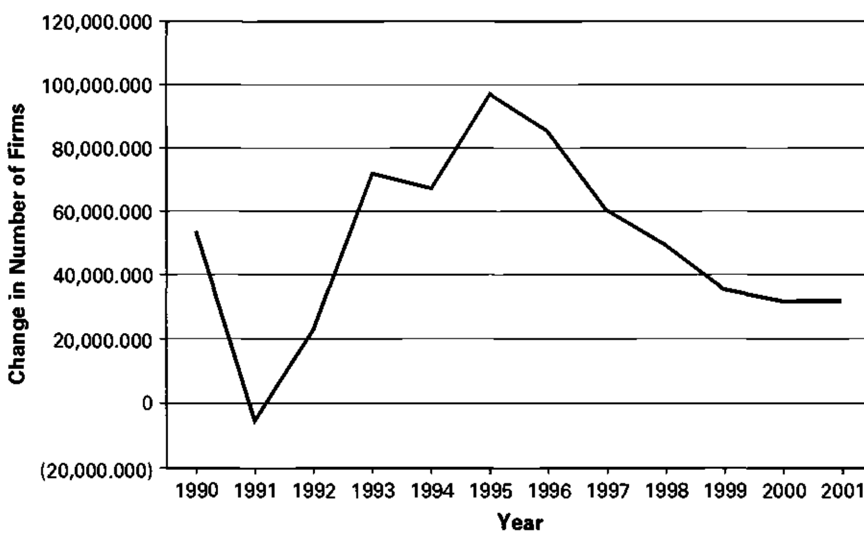

Figure 3.23
Net Change

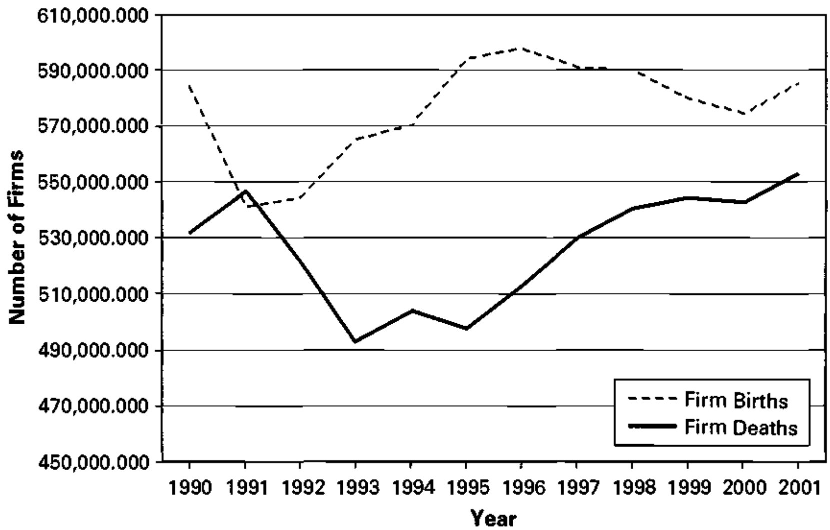

Figure 3.24
SBA Firm Births and Deaths

late 1990s. Figure 3.24 shows that while firm deaths rose after 1995, the number of firm births remained at high levels throughout the period. While certainly not conclusive, this evidence is suggestive of high turnover in smaller (non-publicly-traded) firms.

This increase in volatility during the boom years of the late 1990s stands out against an otherwise countercyclical pattern of volatility in both the financial and real data. This episode also contributes noticeably to the appearance of a trend in volatility over time since the increase in volatility not only continued but accelerated over this period (figure 3.19, for example). Moreover, the most recent data suggests that the turbulence of the 1990s may be reversing itself. Understanding whether this period is an episode or the continuation of a volatility trend may be an important first step to understanding and explaining the interesting set of facts compiled in this paper.

Endnotes

1. Campbell, Lettau, Malkiel, and Xu calculate the standard deviation of monthly returns within a year to obtain the annual standard deviation of the value-weighted index of NYSE, NASDAQ, and AMEX equity returns.

2. This could be the case since the service component of goods may be rising, as may the service component of services.

3. Fama, E., and K. French (2001), "Disappearing Dividends: Changing Firm Characteristics or Lower Propensity to Pay?" *Journal of Financial Economics*, 60:3–43.

4. This is still not a perfect control for compositional change since the composition of incumbents may change through mergers, acquisitions, and even new investments.

5. The CBOE reports annualized daily volatility.

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Discussion

Participant comments focused on increased specialization, increases in the number of firms, and compositional changes.

Xavier Gabaix emphasized the trend within firms toward deagglomeration and increased specialization. This slicing up of the value chain, he argued, could also account for some of the increased firm volatility. Robert Hall echoed this point of increased specialization and connected it to outsourcing. Modern firms rely much more on outsourcing—either internationally or within national borders. He gave as examples Sara Lee's reliance on contract manufacturing sent directly to supermarkets, and Microsoft's contract manufacturing of the Xbox. In Hall's view, the increasing sophistication of the U.S. economy—in particular, financial development—facilitated the contractual relationships necessary for outsourcing and thus contributed to the increase in specialization and the concomitant increase in firm volatility. Thomas Philippon responded that there were in fact many conglomerates started after 1980 that were broken into small pieces by the 1990s. But he noted that increased volatility is also true for single-segment firms in the COMPUSTAT database.

Robert Hall also contended that the different trends in aggregate and firm-level volatility are compelled by the simple fact that there are many more firms than there used to be. If the number of firms had remained constant, and firms were just rescaled as we rescale the economy, then aggregate volatility would remain the same. But any increase in the number of firms automatically means that the trend in firm-level volatility is going to be rising relative to aggregate volatility. If there had been no increase in firm-level volatility, there would have been an even larger decline in aggregate volatility. Thomas Phillipon agreed with this theory but noted that even when you hold the number of firms fixed, you see higher volatility at the firm level.

Regarding composition effects, Xavier Gabaix cautioned that decreasing volatility in both the services and manufacturing sectors does not mean that composition effects are any less important to the declining aggregate volatility. If services are less volatile than manufacturing, and there is a change in composition toward more services, then aggregate volatility will decrease. But if there is feedback from aggregate volatility to sectoral volatility, then the decrease in aggregate volatility will cause the volatility of both manufacturing and services to decrease.

Diego Comin reported that by looking at the aggregate variance decompositions using the KLEM data, the importance of compositional change can be determined. When Comin and Philippon assumed that the shares of sectors are constant, they found that adding up the variance/covariance components gives a very close approximation of aggregate variance. They concluded from this that compositional change is not a big part of the story of the decrease in aggregate volatility.

Comin also reiterated that the variance decompositions show that the important channel is not the variance within a sector but the covariance between sectors. Particularly in the second wave of the KLEM data (1958–1994), the variance component is an order of magnitude smaller than the covariance for the growth of value-added data. Further, there is no evidence of a decline in the variance of sectoral growth, but there is clear evidence of a decline in the correlation of growth across sectors.

Finally, Justin Wolfers suggested using option price data to get an indication of implied or expected volatility and investigating this at the firm level. Thomas Philippon reported that using option-pricing values implied firm-level volatility has come down. Credit spread can also be used as a measure of credit risk, and the downward trend is seen there as well.